2015

Essays on Low-Income Communities and Crime

Kaitlyn R. Harger

Essays on Low-Income Communities and Crime

Kaitlyn R. Harger

Dissertation Submitted to the
College of Business and Economics at
West Virginia University
In partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Economics

Joshua C. Hall, Ph.D., Chair
Brian J. Cushing, Ph.D.,
Donald J. Lacombe, Ph.D.
Amanda L. Ross, Ph.D.
Matt E. Ryan, Ph.D.

Department of Economics

Morgantown, West Virginia
2015

Keywords: capital tax credits, entrepreneurship, crime, recidivism

Abstract

Essays on Low-Income Communities and Crime

Kaitlyn R. Harger

This dissertation is a collection of essays examining issues related to low-income communities and criminal behavior. The first chapter of this dissertation provides an introduction to policies used to aid disadvantaged communities and marginalized populations. It also provides an outline of the research agenda of the dissertation as a whole. Chapter 2 examines the role of the New Markets Tax Credit (NMTC) in attracting new businesses and employment to low-income communities. This federal tax credit program was designed to increase investment in eligible communities by offering private investors a federal-income tax credit in exchange for investment. The results suggest that the program did attract new businesses and employment to these areas, primarily in the FIRE and services industries. Chapter 3 empirically analyses the relationship between tattoo visibility and recidivism for ex-offenders. I construct two measures of visibility, which are dependent on workplace attire. The results from this chapter suggest that inmates with visible tattoos are more likely to return to prison and do so faster and more often than inmates with less-visible tattoos. Chapter 4 examines whether distance between an offender's residence and incarceration facility affects recidivism. Results from OLS regressions and survival analysis both suggest that as distance increases, offenders are less likely to return to prison in the future. Chapter 5 summarizes the findings in chapters 2 through 4 and discusses related future projects in these areas.

Acknowledgements

First and foremost, I would like to thank my husband, Max Harger, for his constant support and encouragement throughout my entire academic career. I am eternally grateful for his belief in my ability to pursue my research interests and my Ph.D. and without his love and reassurance I would not have completed this program.

I would also like to thank my entire dissertation committee for their endless efforts, support, and feedback, all of which helped me complete this dissertation. I am very thankful for my dissertation chair, Joshua C. Hall, for providing me with constant guidance, encouragement, and advice over the last two years. I am very fortunate to have had an advisor who was always willing to discuss my concerns, answer my questions, and send opportunities my way. I am also very grateful to Amanda L. Ross for being a wonderful mentor to me over the last four years. Her constant encouragement to develop my academic skills and to be more professionally outgoing has been invaluable to my career. Donald Lacombe's spatial econometrics course was one of the best classes I took in this graduate program. The lessons I learned in his course reach far beyond spatial econometrics and gave me a better understanding of econometric research. I am also very grateful to have had the support of Brian J. Cushing, who spent an entire summer with me navigating the pedagogy of online courses. He is an extremely devoted teacher and mentor and I am a better scholar and instructor thanks to his efforts. Finally, I was very lucky to have Matt E. Ryan as a professor while I was an undergraduate and he showed me how exciting economic teaching and research can truly be. I am grateful for the time he has taken to provide me with advice and feedback on my progress over the last six years.

Table of Contents

List of Tables

List of Figures

Chapter 1
Introduction

1.1 Public Policy, Low-Income Communities, and Crime

Many communities within the United States face issues related to poverty, unemployment, and crime. As a result, policymakers are constantly searching for ways to eliminate these issues. Federal, state, and local governments all provide programs to try to assist with alleviating problems in low-income communities within the United States.

Location-based policies are one method by which policymakers attempt to increase economic opportunities for residents living in struggling areas. Often the goal of policies of this type is to increase employment opportunities for residents within the targeted areas. A great deal of research has examined how to best achieve the goals of improving communities facing high unemployment, poverty, and crime rates. Some policies within the United States aim to increase employment by subsidizing either capital or labor. One example of a program which provides a labor subsidy is the Empowerment Zone (EZ) program within the United States. Other programs offer tax credits on capital to attract new businesses to struggling areas. I examine one such policy, the New Markets Tax Credit, in the second chapter of my dissertation.

Research on location-based programs' ability to attract new businesses has found mixed results, with some studies finding programs do attract new businesses and others finding no effect. It is possible that industry-specific trends underlying overall results are confounding the findings within these analyses. Given that tax credit programs within the United States are usually a credit on capital or labor, policies of this type should be expected to attract different types of businesses depending on whether they target capital or labor. Analyses that examine the overall effect of policies targeting labor or capital may be missing the underlying industry effects that result from the program.

Recent contributions to the literature by Hanson and Rohlin (2011) and Patrick (2014) argue that there are heterogeneous effects of policies across different types of industries. This suggests that programs which cheapen the cost of capital should be expected to attract firms with more capital-intensive initial costs relative to those with labor intensive costs. For example, if the cost of capital becomes relatively cheaper due to a subsidy on capital, we should expect to see firms in that area take advantage of this cheapened capital by making capital improvements.

Although placed-based programs are often designed to attract new businesses, policymakers only care about new businesses to the extent to which they create new employment. New business growth is one of the key drivers of employment growth for low-income communities. In 2005, approximately 3.5 million new jobs were created by new businesses, dramatically more than any other firm-age category (Haltiwanger et al., 2013). In order to help lagging areas, policy makers at all levels of government enact legislation with the goal of attracting new firms. This idea, known as "economic gardening," is emphasized by Neumark et al. (2007) who stated that "new firms contribute substantially to job creation."

The second chapter of my dissertation examines whether the NMTC program is effective in attracting new businesses and employment to disadvantaged communities within the US. Given that the NMTC is a capital tax credit, an industry-specific analysis of the program's effects contributes to the literature by improving our understanding of the effects of subsidizing capital in low-income communities, potentially at the expense of unskilled labor.

Incarceration and crime rates have also recently received a great deal of attention within US public policy debates. As such, the determinants of criminal activity and incarceration are the focus of many research programs in public policy, criminology, and economics. A particular emphasis has been placed on the analysis of the behavior of repeat offenders with research examining ways to break the cycle of crime.

An increasing area of the literature on crime and recidivism examines the role of employment in breaking this cycle of repeat imprisonment. Ex-offenders are particularly important labor force participants because research suggests that employment post-release is important for reducing the likelihood of criminal activity and incarceration in the future. One area that has received little attention within this research is the role that personal appearance plays in labor force reentry.

Some research has also focused on how prison conditions affect future crimes of inmates, examining whether 'harsher' policies provide better or worse outcomes upon release. One area of debate in this literature concerns whether housing inmates close to home, positively or negatively affects crime in the future. Several previous studies suggest that familial support and visitation while incarcerated is associated with a lower likelihood of recidivism upon release (Bales and Mears, 2008; Duwe and Clark, 2011). However, differential effects may exist depending on the relationship between the inmate and the visitor. For example, Duwe and Clark (2011) find evidence that visits from ex-spouses increase the risk of future criminal activity. Bedard and Helland (2004) present an alternative view, arguing that as prisons are sited in more isolated conditions, the female crime rate declines. They suggest that as the expected distance between home and incarceration facility increases, the likelihood of visitation while incarcerated declines, and as a result women are deterred from committing potential crimes. In chapter 4, I examine how the experience of being housed far from home affects the future criminal behavior of offenders.

1.2 Dissertation Research Agenda

There are three research essays included in this dissertation that examine the effects of public policy on low-income communities and crime. The first essay, Chapter 2, is coauthored with Amanda Ross and examines the role of a specific place based-policy on new business location in low-income communities. Chapter 3 looks at the role that visible tattoos play in the likelihood that an ex-offender returns to prison and chapter 4 focuses on how distance between an offender's residence and prison may affect future recidivism rates. Chapter 5 concludes with an overview of the findings presented in chapters 2 through 4.

In the second chapter of my dissertation Amanda Ross and I examine whether the New Markets Tax Credit Program (NMTC) attracts new businesses or employment to distressed communities in the United States. The Community Renewal Tax Relief Act of 2000 first established the NMTC program, and the tax credit has been renewed every year since implementation. While the program was established in 2000, the first tax credits were not allocated until 2003 (Freedman, 2012; Abravanel et al., 2013). The goal of the program was to combine government and private funds to increase investment in low-income communities by $15 billion over the next five years (Groves, 2006; Rubin & Stankiewicz, 2005). Although the NMTC program is similar to other location-based tax incentives, it is somewhat unique in that it aims to increase investment in eligible communities by using tax credits to mitigate some of the risk of opening a business in a low-income area. However, the tax credit is not large enough to remove all risk and is likely to avoid overinvestment (Freedman 2012).

While firms could receive the NMTC for various types of investment, in practice the majority of the funds went towards capital investments. The tax credit could be used for labor expenses, typically referred to as "business purposes," but this type of expenditure was infrequent. The tax credit was allocated over seven years, and to renew the credit certain criteria had to be verified each year. Given the yearly requirements that firms had to meet to keep the tax credit, as well as the abundance of other tax credits available for labor purposes, most of the funds allocated through the NMTC went towards capital expenditures. According to Abravanel et al. (2013), 46% of the projects funded by the NMTC were used for office, retail, mixed use, or hotel development. The remaining projects were split up as follows: 22% to social services, educational, or cultural/arts use, 18% to manufacturing, industrial, or agricultural uses, 9% to health facilities, and 5% to housing. This breakdown of the expenditures of the program further demonstrates that the tax credit allocations went towards more capital intensive projects.

We use the New Markets Tax Credit (NMTC) to determine the effect of a capital tax credit on where firms in different industries locate. When estimating the impact of the tax credit on business location, there are likely to be unobservable local characteristics that are correlated with business location decisions that would cause OLS estimates to be biased. To control for this endogenous selection, we use a plausibly exogenous eligibility cutoff and compare census tracts that are just eligible for the NMTC to those that are just ineligible. Using data from the Dun and Bradstreet MarketPlace Files, we find that in Metropolitan Statistical Areas, the NMTC incentivized new businesses to locate in tracts that were eligible for the tax credit. However, we find that these positive effects on employment are concentrated in a few industries, specifically services and financial services, insurance, and real estate. This result is consistent with previous work that has argued capital tax credits may have negative impacts on employment, as the program changes the relative price of capital and may cause firms to substitute away from low-skilled workers towards capital investment. Our results are important for policy makers, as we find that capital tax credits have adverse consequences on labor markets for some industries.

Chapter 3 focuses on the relationship between recidivism and one aspect of an ex-offender's personal appearance, visible tattoos. Many ex-offenders have visible tattoos which may limit their employment opportunities. Conventional wisdom suggests that individuals with tattoos visible in the workplace may have fewer employment opportunities than people with similar qualifications and no visible tattoos. Visible tattoos may create even more of an employment barrier for the ex-offender population because potential employers may interpret the tattoos (correctly or incorrectly) as signals of criminality.

Research on criminal signaling mechanisms details how some criminals use tattoos as a visual résumé for their prior criminal acts (Gambetta, 2009). If employers are aware that tattoos are used to signal criminality, then while interviewing potential employees from a pool of ex-offenders, non-tattooed or non-visibly tattooed ex-offenders may seem more reformed than ex-offenders with visible tattoos. In this chapter, I examine whether inmates with visible tattoos return to incarceration faster than non-tattooed inmates.

Two recent criminology studies also attempt to estimate the relationship between visible tattoos and recidivism. Lozano et al. (2010) consider a small sample of inmates with prison tattoos, inmates with non-prison tattoos, and college students. The results from their study suggest that inmates with prison tattoos score higher on recidivism risk assessments than inmates without prison tattoos and college students. Waters (2012) expands upon Lozano et al. (2010) using data from the FDOC and examines the relationship between visible tattoos and the occurrence of recidivism within the last three years. The results suggest that inmates with visible tattoos are more likely to be reconvicted for new felony offenses and new violent offenses within three years.

Although these studies take a first step at linking tattoos to recidivism, both have important limitations. Lozano et al. (2010) use a sample of 274 inmates and college students and examine the correlations between tattoo and criminal history variables. It is possible that the relationships found within their data are a function of this small sample size. Additionally, no regression analysis is used within their study, so they are unable to control for other factors related to recidivism. Waters (2012) builds on the work by Lozano et al. (2010) using logistic regressions to examine the likelihood of recidivism for inmates based on tattoo visibility. However, Waters (2012) considers only whether or not an inmate returned to prison, and fails to account for the timing of recidivism within the three year follow-up period. In that case, an inmate who returns to prison on the last day of the three year period he considers is treated identically to an inmate who returns to prison on the first day post-release.

I contribute to this literature by examining the relationship between visible tattoos and recidivism. Conventional wisdom suggests that some employers may choose not to hire applicants with visible tattoos, assuming the tattoos signal something unobservable about the potential employees. Additionally, research on recidivism suggests that employment post-release is a main determinant of whether an ex-offender returns to prison. Combining these two literatures suggests a relationship may exist between visible tattoos and the number of days an ex-offender lives in society without returning to prison. Using data from the Florida Department of Corrections, I estimate a log-logistic survival model and compare the estimated number of days until reincarceration for inmates with and without visible tattoos. The findings suggest that inmates with visible tattoos return to incarceration faster than those without tattoos or with tattoos easily hidden by clothing. This suggests that programs advocating for tattoo removal or coverage during interviews may be helpful for increasing employment chances and reducing recidivism.

In Chapter 4, I examine the relationship between distance between residence and incarceration and recidivism. Findings from criminological research on prison visitation suggests that visitations serve to decrease the likelihood of recidivism in the future as they allow the inmate to keep in contact with family and friends while in prison (Liu et al., 2014). This continued connection with the outside world allows the inmate to maintain social ties which can potentially affect recidivism risk post release. However, the mechanism through which recidivism risk is affected may be dependent on the relationship between the inmate and visitor.

These previous studies suggest that when visitations do occur, they have the potential to decrease future criminal activity. However, not all inmates receive visits while incarcerated. Duwe and Clark (2011) report that 39% of inmates are never visited during incarceration. A variety of factors, including individual characteristics may affect whether or not an inmate receives visitors while serving time. A main barrier to visitation reported by relatives and friends of prisoners is the cost of transportation to the prison (Bedard and Helland, 2004).

The potential effects of serving time in an isolated condition on an inmate's social connections are well documented within the literature. However, the relationship between distance and crime has received far less attention. Bedard and Helland (2004) use natural variation in the expansion of women's prisons to examine the effects of prison isolation on female crime rates. Their results suggest that an increase the expected distance between residence and incarceration facility causes a decrease in the female crime rate. This evidence of the deterrent effect of prison isolation is in line with Becker's (1968) theory of the economics of crime.

In Chapter 4, I examine how the distance between incarceration facility and residence is related to the likelihood of recidivism for an inmate. Research suggests that as the distance between prison and home increases, the likelihood of visitation while incarcerated decreases. This lack of visitation at geographically isolated prisons has been shown to have a deterrent effect on crimes committed by female offenders. However, if the deterrence is driven by the inability to consume utility from visitation, then all offenders should be less likely to commit crimes as the expected distance increases. Using data from the Florida Department of Corrections (FDOC) Offender Based Information System (OBIS), I estimate a survival model to examine the relationship between distance and the timing and occurrence of recidivism. The results suggest that inmates incarcerated farther away from home survive in society longer before reincarceration. Specifically, a one standard deviation increase in distance is associated with a 166 day decrease in the expected number of days before an inmate returns to prison. This result is consistent with previous work which finds that geographic isolation of prison serves as a deterrent effect for female offenders. The findings within this paper are important for policy makers in search of cost effective ways to reduce future crime.

Chapter 2

Do Capital Tax Incentives Attract New Businesses? Evidence across Industries from the New Markets Tax Credit

2.1 Introduction

New businesses are considered to be a key driver of local economic growth in the United States. Since new establishments are so important to the local economy, policy makers design tax programs to attract new businesses with the hope that these enterprises will drive future growth within their jurisdiction (Neumark et al., 2007). These tax policies are typically place-based policies, where a business is eligible to receive the credit if it locates in a specific area, typically low-income or high-poverty census tracts. In general, research that has estimated the impact of tax policy on where businesses locate has produced mixed results, with some researchers finding tax credits attract new establishments while others find no significant effect.[1]

One explanation for the discrepancy regarding the effect of place-based programs on business location decisions is that there are heterogenous effects of policies across different types of industries (Hanson & Rohlin, 2011b; Patrick, 2014). For example, the government could offer a tax credit to firms that locate in a specific area and hire workers from that jurisdiction.[2] A program such as this effectively creates a labor subsidy for businesses to locate in the area, so we expect industries that are more labor-intensive to outbid industries that are more capital-intensive for land in the area that are eligible for the tax credit.

---

[1] For example, there is an extensive literature that has looked at the impact of the Enterprise Zone program on business location decisions (see Oakley & Tsao (2006), Hanson (2009), Krupka & Noonan (2009), Hanson & Rohlin (2011a) and (2011b), and Busso, Gregory, & Kline (2013) for more information)

[2] This type of program would be similar to the Enterprise Zone (EZ) program, though there are other conditions of the EZ program which we do not consider in this simple example.

In this paper, we use the New Markets Tax Credit (NMTC) to determine the effect of a capital investment tax credit on the location decisions of new businesses and employment. We consider not only the effect of the policy on all types of establishments, but also how the effect of the policy varies across firms in different industries. The NMTC, which was passed in 2000 but the first credits were not allocated until 2003, provides a tax credit to businesses to make investments in low-income communities.[3] While the NMTC could be used for a variety of purposes, including labor expenses, in practice the credit was used primarily for capital investments, so we will refer to this program as a capital tax credit.[4]

One of the issues when estimating the effect of a place-based tax credit on business location decisions is that there is likely to be a non-random selection of communities by both businesses and policy makers. First, businesses choose which neighborhood to locate in based on numerous local attributes, some of which are observable, such as the poverty rate and racial composition, and others that are unobservable, such as agglomeration economies. If these unobserved attributes are correlated with where the NMTC is allocated, then simple OLS estimates would produce biased results. Second, there is a selection process with regards to which businesses receive the tax credit. Not all applicants for the NMTC receive the credit. Therefore, to compare those businesses that received the tax credit to those that did not would be problematic if firms were selected for the program based on expected growth in the local area.

---

[3] Other papers that have looked at the economic impact of the NMTC are Gurley-Calvez et al. (2009), Freedman (2012), and Freedman (2013). We discuss each of these papers in more detail later.

[4] The NMTC could be used for labor expenses, commonly referred to in the program as "other business" expenses. However, due to the required materials to receive the NMTC over the entire life of the program, most applicants did not apply for labor assistance. In addition, most other existing tax credit programs are aimed at hiring workers. Given the flexibility of the NMTC, many project managers argued it was their only source of funding for capital expenditures, whereas labor expenditures could be funded by other programs. As a result, in practice the majority of projects used the NMTC for capital expenditures. For more information on the types of projects these funds went to, please see http://www.gao.gov/assets/670/664717.pdf and http://www.taxpolicycenter.org/UploadedPDF/412958-new-markets-tax-final.pdf.

To control for these factors and obtain causal estimates, we draw upon a plausibly exogenous eligibility cutoff in the NMTC to determine whether or not the program attracted new business activity. Eligibility for the NMTC program is based on the ratio of the census tract median family income (MFI) to the state MFI or MSA MFI, whichever is higher, which we refer to as the income eligibility ratio. To be eligible to receive the NMTC, the income eligibility ratio in a given census tract must be less than or equal to 0.80.[5] We use whether or not a census tract falls just above or below this cutoff as exogenous variation to estimate the effect of the NMTC on business location decisions. Note that we do not know whether or not a specific business was allocated the tax credit, only if a business that located in a tract that was eligible to receive the credit. By comparing business activity in tracts that just qualify to receive the NMTC to those that just fail to qualify, we are able to control for unobserved local attributes. In addition, by focusing on eligibility, not the actual allocation of the tax credit, we are able to remove any concerns regarding the endogenous selection of which businesses received the tax credit.

To conduct our analysis, we use data from the Dun and Bradstreet (D&B) MarketPlace files from the second quarter of 2002, 2004, and 2006. We focus on tracts located in MSAs, as existing research has shown that there are fundamental differences between urban and rural development (Stephens & Partridge, 2011; Rupasingha & Goetz, 2013; Stephens, Partridge, & Faggian, 2013).[6] In addition, approximately 91% of the projects that received the tax credit went to tracts in MSAs (Abravanel et al., 2013). The D&B data contains a wealth of information on

[5] We will discuss in detail the specifics of the NMTC program and the eligibility for the program later in the paper.
[6] Rural areas may lack the economies of scale associated with agglomeration and thus business owners may not fully capture the same benefits that they would have in urban areas (Stephens & Partridge, 2011; Rupasingha & Goetz, 2013; Stephens, Partridge, & Faggian, 2013). Also, while eligibility for the NMTC is primarily based on the median income of a tract, rural areas can qualify under additional criteria that were added in 2004. Specifically, rural tracts can be eligible for the credit if there is high out-migration or if there have been significant population declines.

establishments at the ZIP code level, including the SIC code of each business.[7] In addition, the D&B data has information on how long each business has been open. Throughout the paper, we define a new business as an establishment that has been open for less than one year and an existing business as an establishment that has been open for four or more years.[8]

When we estimate the effect of the NMTC on businesses across all MSA census tracts, we find that businesses are less likely to locate in those tracts that are eligible to receive the tax credit. However, businesses are generally more likely to prefer to locate in areas with lower poverty rates and higher incomes, and these areas are not eligible for the NMTC. These higher income tracts that are ineligible for the program are likely to have unobservable attributes that are substantially different from those low-income tracts that are eligible for the tax credit. To address this issue, we restrict the sample to those census tracts that are just above and just below the 0.80 income eligibility ratio. We focus first on those tracts that have an income eligibility ratio between 0.70 and 0.90, and then further restrict the sample to those with an eligibility ratio between 0.75 and 0.85.[9] Overall, we find that when we consider only those tracts near this 0.80 eligibility ratio, there is an increase in both new businesses and new business employment in the tracts that are eligible for the NMTC.

As mentioned earlier, the NMTC is a capital tax credit, so it is possible that the credit will have heterogenous effects across industries. More specifically, the NMTC was allocated to firms primarily for capital expenditures, such as real estate and building space (Abravanel et al., 2013). When we stratify our results by industry, we find the effects on new employment seem to be

[7] When a business is classified under more than one SIC code in the Dun and Bradstreet data, we classify the establishment according to its primary industry code.
[8] We choose four years as 45% of businesses fail in the first eighteen months (BLS, 2015). This allows us to measure what we consider to be established firms, as we believe this is a strong indicators of growth and economic well-being of the area.
[9] We have run models further restricting the sample to be those tracts within 0.79 and 0.81 of the income eligibility ratio. Those coefficients are similar to those presented below, but due to the decreased sample size tend to have larger standard errors. These results are available from the authors upon request.

most concentrated in services and FIRE. Given that FIRE includes real estate firms, this result is expected as one of the largest expenditures of the program was real estate investments. The services industry includes a variety of sub-industries, including educational and social services, which are also two of the main areas that the tax credit was allocated towards (Abravanel et al., 2013). However, when we look at the effect on new establishments, we find strong evidence of a positive effect on the number of new establishments across all industries, except construction and transportation. This finding of a positive effect on the number of establishments but limited effects on employment is consistent with the work of McCulloch and Yellen (1977) which argues that capital tax credits create a substitution away from low-skilled labor towards capital investment. Our results are consistent with the prediction that programs such as the NMTC that are aimed at helping lagging areas may have some perverse effects as the policy may incentivize firms to reduce the number of low-skilled workers employed.

We also consider the impact of the policy on existing firms. When we look at existing firms, we see no effect of the policy on the level of employment in existing firms. However, when we look across industries we find an increase in employment in existing construction firms, retail, and FIRE. This result suggests that construction firms had to hire more workers to take on the additional projects created by the tax credit. The positive effect on retail and FIRE suggests that these industries may have expanded to account for the increased number of firms and employees in the area. Overall, our finding supports previous work that has found that the impact of government programs varies based on whether the policy favors investment in capital or labor (Hanson & Rohlin, 2011b; McCulloch & Yellen, 1977; Patrick, 2014).

The rest of the paper proceeds as follows. Section 2.2 describes in detail the specifics details of the NMTC program. Existing research on place-based tax programs and the NMTC in particular are discussed in Section 2.3. Our empirical strategy is outlined in Section 2.4 and in Section 2.5 we discuss our data. Section 2.6 contains our results. We conclude and discuss policy implications in Section 2.7.

2.2 The New Markets Tax Credit[10]

The Community Renewal Tax Relief Act of 2000 first established the NMTC program, and the tax credit has been renewed every year since implementation. While the program was established in 2000, the first tax credits were not allocated until 2003 (Freedman, 2012; Abravanel et al., 2013).[11] The goal of the NMTC program was to combine government and private funds to increase investment in low-income communities by $15 billion over the next five years (Groves, 2006; Rubin & Stankiewicz, 2005). Although the NMTC program is similar to other location-based tax incentives, it is somewhat unique in that it aims to increase investment in eligible communities by using tax credits to mitigate some of the risk of opening a business in a low-income area. However, the tax credit is not large enough to remove all risk and is likely to avoid overinvestment (Freedman 2012).

The NMTC is managed by a division of the U.S. Treasury department known as the Community Development Financial Institutions (CDFI) Fund.[12] The goal of the CDFI fund is to increase community development and economic opportunities for distressed areas within the United States. Since the inception of the NMTC, the CDFI fund has awarded roughly $36.5

[10] The information from this section, unless otherwise cited, comes from resources found at www.cdfifund.gov.

[11] Applications were accepted for the first year of the program beginning in July 2002. See http://www.cdfifund.gov/docs/2002_NMTC_NOAA.pdf for more information on when applications became available and when the applications were accepted.

[12] For more detailed information of the CDFI Fund please see http://www.cdfifund.gov/who_we_are/about_us.asp.

billion in tax credits through the program.[13] Table 2.1 provides information on the total amount allocated through the NMTC program from 2001 to 2012.

Table 2.1: Total NMTC Allocations

Year	Total Allocation
2001-2002	$2,485,699,042.00
2003-2004	$3,493,786,205.00
2005	$1,964,830,000.00
2006	$4,099,765,000.00
2007	$3,893,000,000.00
2008	$4,965,000,000.00
2009	$5,000,000,000.00
2010	$3,475,000,000.00
2011	$3,622,919,753.00
2012	$3,500,000,000.00

Notes: The information on the allocations was obtained from the CDFI website, http://www.cdfifund.gov/docs/nmtc/2014/NMTCQEI_Report_042014.pdf. During the first two years of the program, although Congress provided allocations to the program, no allocations were to CDEs until 2003 as start-up tasks delayed the process. The allocations awarded to the NMTC program by Congress in 2001 and 2002 were combined and awarded by the CDFI fund to CDEs in 2003. The allocations awarded to the NMTC program in 2003 and 2004 were then combined and dispersed to CDEs in 2004. See http://www.gao.gov/new.items/d07296.pdf for more information on the allocations awarded.

While firms could receive the NMTC for various types of investment, in practice the majority of the funds went towards capital investments. The tax credit could be used for labor expenses, typically referred to as "business purposes," but this type of expenditure was infrequent. The tax credit was allocated over seven years, and to renew the credit certain criteria had to be verified each year. Given the yearly requirements that firms had to meet to keep the tax credit, as well as the abundance of other tax credits available for labor purposes, most of the funds allocated through the NMTC went towards capital expenditures. According to Abravanel et al. (2013), 46% of the projects funded by the NMTC were used for office, retail, mixed use, or

[13] Specific statistics on the allocation amounts of the tax credit were taken from the CDFI Fund's website, www.cdfifund.gov.

hotel development. The remaining projects were split up as follows: 22% to social services, educational, or cultural/arts use, 18% to manufacturing, industrial, or agricultural uses, 9% to health facilities, and 5% to housing. This breakdown of the expenditures of the program further demonstrates that the tax credit allocations went towards more capital intensive projects.

The CDFI administers tax credit allocations to qualified Community Development Entities (CDEs) which then disperse the funds to private investors in targeted areas (Freedman 2012, Abravanel et al. 2013, Freedman 2013).[14] CDEs consist of domestic corporations or partnerships that serve as intermediaries between investors and Low-Income Communities (LICs). In order to qualify as a CDE, a corporation or partnership must apply for certification through the U.S. Treasury's CDFI fund.[15] Only businesses listed as corporations or partnerships for federal tax purposes are eligible for CDE certification.[16] Once certified as a CDE by the CDFI Fund, the certification remains valid for the lifetime of the business provided it continues to comply with specific requirements. The certification requirements detail only what is required to qualify as a CDE. Additional requirements and reports may be obligatory to receive the tax credit allocations depending on the type and amount of investment a CDE receives.

To meet the requirements for certification by the CDFI fund, the primary focus of a CDE must be to increase the amount of investment available to LICs. More specifically, at least 60 percent of the firm's financial activity must be directed towards aiding LICs.[17] In addition, qualification as a CDE is contingent upon community-resident representation on any advisory

[14] The process by which a CDE determines which investors will receive investment funds may vary widely across CDEs. It is possible that in some areas CDEs do not receive many applications and thus have very relaxed standards processes and in other areas the application process may be more competitive. Without more information about individual CDEs and the constraints under which they operate, it is impossible to disentangle these differences.

[15] For more information on the CDE certification process, please reference the CDE certification application found at http://www.cdfifund.gov/docs/certification/CDE/CDE%20Certification%20Application_01222013.pdf

[16] Limited liability companies and sole proprietorships are not eligible for CDE status. Government entities listed as partnerships or corporations for Federal income tax purposes are eligible to apply for CDE certification.

[17] See http://www.cdfifund.gov/docs/certification/CDE/CDEcertificationFAQs.pdf for more information on the rules regarding the allocation of tax credits.

board within the organization (Freedman 2012). The purpose of the advisory board requirement is to ensure accountability to the residents of the LICs. CDEs accept qualified investments for use in low-income communities from private investors and in turn supply those investors with the tax credit. If awarded a NMTC allocation, individual investors receive a federal income tax credit totaling 39% of the initial investment over seven years.

When the NMTC program was initially created, a census tract could qualify as a LIC if it met one of two criteria. The first criterion is based on the median income of the tract. Non-MSA census tracts are eligible for LIC designation if the ratio of the census tract median family income (MFI) to state MFI is less than or equal to 80%. Census tracts located within an MSA qualify for LIC status if the ratio of the tract MFI to the larger of the state or MSA MFI, is less than or equal to 80%. Census tracts can also qualify based on the poverty rate, where tracts with poverty rates of 20% or higher are designated as LICs.

In 2004, a revision was made to the NMTC program that added two additional qualification criteria – the low-population criterion and the out-migration criterion. A tract qualifies on the low-population criterion if it contains fewer than 2,000 people, is located within an empowerment zone, and is contiguous to at least one other LIC (Freedman, 2012; Abravanel et al., 2013). A tract qualifies on the migration criterion if it is located in a rural county with high out-migration, where high out-migration is defined as a net out-migration from the county of at least 10% of the county's population at the beginning of the census from twenty years ago to the most recent census.[18] This change allowed CDEs to invest in businesses that are not located in LICs if these businesses serve other targeted populations.[19] Of all the tracts that

---

[18] For a list of census tracts which qualify on the out-migration criteria please see http://www.cdfifund.gov/what_we_do/resources/ListofQualifyingNMTCCensusTractswithinHighMigrationRuralCountiesMay12012.pdf

[19] See www.cdfifund.gov for more information on the different targeted populations.

qualified as LICs, approximately 98% qualify on the income or poverty criteria, and the remaining 2% qualify as either low-population or high out-migration tracts (Freedman, 2012).

Previous Research

Local Economic Development Policy and Business Location

State and local policy makers strive to attract new businesses, as these establishments are crucial drivers of growth for the U.S. economy. In 2005, approximately 3.5 million new jobs were created by new businesses, dramatically more than any other firm-age category (Haltiwanger et al., 2013). In order to help lagging areas, policy makers at all levels of government enact legislation that incentivizes new businesses to open in these struggling areas. This idea, known as "economic gardening," is emphasized by Neumark et al. (2007) who stated that "new firms contribute substantially to job creation."[20]

However, there are questions regarding the best way to set up incentives to attract new businesses to an area. Some argue that location-based programs are the optimal policy to incentivize businesses to locate in a specific area. Glaeser (2001) argues that attracting new businesses to an area will generate economic surplus for current residents in the targeted area. Furthermore, he suggests that offering location-based tax incentives may be justified as the incentives compensate new businesses for future tax payments that will be made to the locality. This research is likely to be one of the reasons why policy makers offer location based tax incentives to attract new establishments to a specific jurisdiction.

Numerous papers have looked at the impact of various types of government policy on business location decisions. Kolko and Neumark (2008) use the National Establishment Time

[20] There is an extensive literature estimating the effect and presence of agglomeration economics and the benefits to businesses of locating in areas with a large amount of economic activity (Arzaghi & Henderson, 2008; Duranton & Puga, 2004; Puga, 2010; Rosenthal & Strange, 2003; and Rosenthal & Strange, 2005).

Series (NETS) database to track the movement of both businesses and employment into and out of California as a result of differences in state policy. Other researchers have used establishment level data to determine the impact of state tax policy on business location (Gabe & Bell, 2004; Rathelot & Sillard, 2008; Duranton, Gobillon, & Overman, 2011; Bruce & Deskins, 2012; Rohlin, Rosenthal, & Ross, 2014). Patrick (2014) created an index to capture the degree to which state constitutions are constructed in a manner that allows state governments to offer non-tax incentives to attract new businesses.[21]

Sectorial Variation in Business Location

While an extensive literature has examined the relationship between firm location and local economic policy, it is possible that the effect of different programs varies based on the specifics of the policy and the industry of the business. This relationship was formalized by Hanson and Rohlin (2011b) who examined the impact of Enterprise Zones (EZ) on where businesses located based on the industry of the establishment. The EZ program is a tax credit given to businesses to locate in struggling areas and to hire workers from that area, causing the program to be a tax credit on labor. Hanson and Rohlin (2011b) developed a theoretical model that showed that more labor intensive industries, such as retail and services, will be willing to bid more for land to locate in those areas that qualify for the EZ tax credit than more capital intensive industries, such as manufacturing. The results of their analysis support this theoretical model, and suggest that there are differential effects of the policy based on how capital or labor intensive the industry is.[22]

In this paper, we focus on a capital tax credit, which may not have quite the same effects on employment across different industries as a labor tax credit. An implication of a capital tax

[21] For a recent review of the methods used in this literature, see Arauzo-Carod et al. (2010).

[22] Patrick (2014) looked at the impact of capital subsidies, versus tax credits, and found that effects of the subsidies varied across industries in the expected manner based on the predictions of Hanson and Rohlin (2011b).

credit is that by reducing the price of capital, we have changed the price of capital relative to labor. Therefore, it is possible that these investments in capital improvements may come at the expense of unskilled labor, which tends to be highly substitutable with capital. This theory of the substitutability of capital and unskilled labor in response to capital subsidies was formalized by McCulloch and Yellen (1977). Their model suggests that when tax or subsidy programs cheapen the cost of capital, firms may respond by improving capital at the expense of workers. Therefore, it is important to consider the effect of a capital tax credit across industries to see which of these two possible mechanisms is present and dominant.

New Markets Tax Credit

First implemented in 2001, the NMTC has been renewed every year since it was enacted by Congress. Despite the longevity of this program, little research exists examining the impacts of the NMTC. Gurley-Calvez et al. (2009) analyzed whether there was an increase in new investment as a result of the NMTC or if investors simply reallocated investments intended for a non-qualifying tract into a qualifying tract. The authors use an instrumental variables approach to determine the effect of the policy and find that some new investments come from individual filers. However, they find that corporate filings, which comprise most of the NMTC recipients in their sample, are unlikely to represent new investment.[23]

Freedman (2012) examined the impact of the NMTC on the communities that received tax credit allocations. To address the endogenous selection process, he uses the income eligibility criteria and an instrumental variables approach to determine whether the NMTC program caused improvements in the LICs to which the credit was allocated. Using census tract

[23] Rubin & Stankiewicz (2009) and Hicks & Faulk (2012) also provide evidence that the NMTC created investment in areas that were eligible for the credit. However, their analysis did not address the endogenous selection of which investments receive the tax credit.

level data to examine several neighborhood outcomes, he finds that the NMTC program had some positive impacts on eligible communities, such as reductions in the unemployment and poverty rates.

Freedman (2013) explores another possible avenue through which the NMTC could impact local jurisdictions – regional labor markets. Exploiting the same discontinuity in the income eligibility criteria, combined with data from the CDFI Fund and employment data from OnTheMap, Freedman (2013) examines whether NMTC eligibility affects the distribution of employment across residents of LICs. His results suggest that to the extent to which new jobs are created in these targeted communities, few go to residents of the eligible low-income communities. However, the findings do not account for the possibility of improvements in LICs as a result of the new investment through mechanisms other than direct employment effects.

We contribute to this growing literature and test whether or not the NMTC attracts new businesses and employment to LICs. In addition, we examine whether the program has industry-specific effects, given that the NMTC is a capital investment tax credit and might have a heterogenous effect across different types of businesses.

2.3 Empirical Strategy

When estimating the effect of the NMTC on business location decisions, there are two selection processes that must be considered. First, businesses select locations based on various local attributes, many of which are unobservable. Second, not all applicants received the tax credit, so simply comparing those that received the credit to those that did not is problematic as businesses are likely to select locations based on their growth potential.[24] To address these concerns, we draw upon a plausibly exogenous eligibility cutoff that determines whether or not a census tract is eligible to receive the NMTC. We do not consider whether or not a specific business received the tax credit, we only consider if more businesses locate in eligible versus ineligible tracts. Given that the goal of the program is for the NMTC to drive continual growth, the overall effect on new business activity is important to consider.

As described above, to be eligible to receive the NMTC, the ratio of the median income in a given census tract to the state median income must be less than 0.80.[25] We draw upon this plausibly exogenous cut-off in eligibility for the tax credit and compare activity in tracts that were eligible to those that were ineligible. Using data on whether or not a census tract is eligible for the tax credit, we initially run the following regression across all MSA census tracts:

$$y_{ij2} - y_{ij1} = \beta_1 elig_i + \beta_i(X_{i2000}) + f(m) + \gamma_j + \delta_s + \varepsilon_{it}.$$

Where *i* indicates a census tract, *j* indicates the two-digit SIC code, *2* designates the year following the enactment of the NMTC, which may be 2004 or 2006, and *1* designates 2002. $y_{ij2} - y_{ij1}$ is the difference over time within a given census tract in the number of new business activity in a given industry, and X_{i2000} is a set of controls for other socio-economic attributes of the tract, including percent black, percent Hispanic, average age, average income, education measures, and percent female. Note that when considering new business activity, we look at

[24] Note that we do not have data on whether or not a specific firm received the tax credit. All we know is whether or not the area is eligible for the tax credit. This means that there are two effects possible – the direct of effect of those firms that receive the tax credit and the indirect effect of the new firms receiving the tax credit attracting other firms to the area. Given the nature of our data, we are unable to separate out these two effects.

[25] For tracts located in MSAs, eligibility is established based on the state median income or the MSA median income, whichever is higher. We account for this distinction in our analysis but for ease of discussion only mention the state median income in the text.

both the effect on the number of new establishments, as well as employment at these new establishments. We also include industry fixed effects, γ_j, at the two-digit SIC code and state fixed effects, δ_s. Our variable of interest is $elig_i$, which indicates whether or not a specific census tract is eligible for the NMTC. $f(m)$ is a control function which allows for the relationship between the MFI and new businesses to be non-linear.[26] We have experimented with multiple specifications of this control function, and the linear relationship was shown to be the best fit.[27] ε_{it} is an idiosyncratic error term.

When examining where businesses locate, there are likely to be unobservable attributes of the local jurisdiction that affect where a new enterprise opens (Puga, 2010; Rosenthal & Strange, 2003, 2005; Arzaghi & Henderson, 2008; Duranton & Puga, 2004). For example, we cannot obtain data that controls for the local agglomeration economies that may benefit firms in the area. Therefore, when we run the above regression for the entire sample, there are likely to be unobservable local attributes that are correlated with business location decisions that may bias our estimates.

To control for these unobservable variables, we draw upon a plausibly exogenous cutoff set by the government regarding eligibility for the NMTC program and compare census tracts that are just eligible for the tax credit to those that are just ineligible. Using this boundary, we are able to compare similar areas and control for unobserved attributes of the locality. Recall that for a tract to be eligible for the NMTC, the ratio of the median family income in the census tract to the state median family income has to be less than or equal to 0.80. We draw upon this

[26] Given the nature of our control function, we are assuming a sharp discontinuity in the treatment because we define treatment as being eligible for the tax credit. This is consistent with our identification, as we do not know exactly which tracts receive the tax credit and rely only on the eligible or not eligible criteria as our treatment.
[27] Using the AIC criteria, we determined that the linear specification was the best fit for the regression. We have experimented with higher order polynomials as well, and the results are consistent but are not shown in the interest of space. These results are available from the authors upon request.

cutoff in the income eligibility criterion and compare census tracts with an eligibility ratio just above and just below 0.80, as these areas are likely to have similar unobservable characteristics.[28] Initially, we restrict the sample to those tracts with a ratio between 0.70 and 0.90 and then further restrict the sample to those tracts with a ratio between 0.75 and 0.85.[29,30]

Our identifying assumption is that prior to the change in policy, there was no systematic difference in those tracts just above and just below the 0.80 income eligibility cutoff. To justify this assumption, we need to show that there was nothing unique about the 0.80 cutoff prior to the policy change. While the law was passed in 2000, applications did not start being accepted until July 2002 and funds were not allocated until 2003. Therefore, we use the second quarter of 2002 as our pre-period, as it is unlikely new businesses formed as a result of the tax credit since the announcement of the awards had not yet been released.[31] Looking close to the 0.80 boundary in 2002, we show in Figure 2.1a that there is nothing unique about this boundary, as the number of employees at new establishments appears to be continuous across the boundary. In Figures 2.1b and 2.1c we look at this same portion of the income eligibility ratio in 2004 and 2006. We see that in those years there is a clear jump in new employment at this boundary, suggesting that the policy had an effect on the relative attractiveness of one side of the boundary to the other.

---

[28] Similar boundary type regressions have been used in other applications in the literature, such as Holmes (1998), Levitt (1998), and Black (1999).

[29] A tract can be eligible for the NMTC based on either the eligibility ratio or the poverty rate in the tract. However, few tracts qualify based on the poverty criterion alone. Freedman (2012) showed that approximately 70% of tracts that have a poverty rate between 15-20% qualify for the NMTC based on the income eligibility criterion. Therefore, since the poverty rate criterion does not appear to be the determining factor for eligibility in the NMTC, we focus on the income eligibility criterion.

[30] Data on where the individual investments were made is not currently publically available. It is possible to obtain information on the address of the CDEs, but we are unable to determine the tract where the investments were made.

[31] As a robustness check, we use 1994 as our pre-period later in the paper and the results are consistent.

Figure 2.1a: Average Number of New Employment in 2002 over the Eligibility Ratio

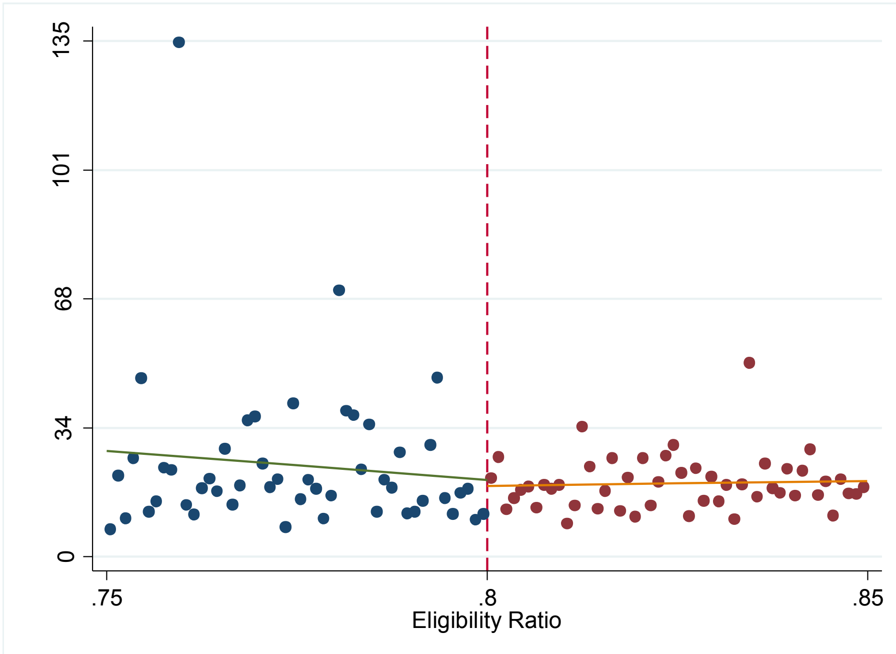


Figure 2.1b: Average Number of New Employment in 2004 over the Eligibility Ratio

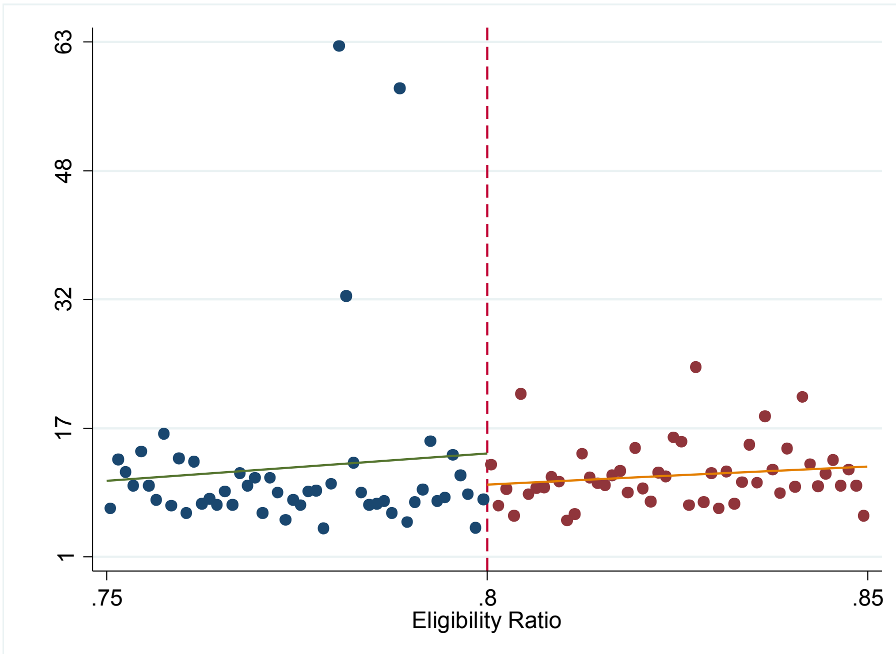
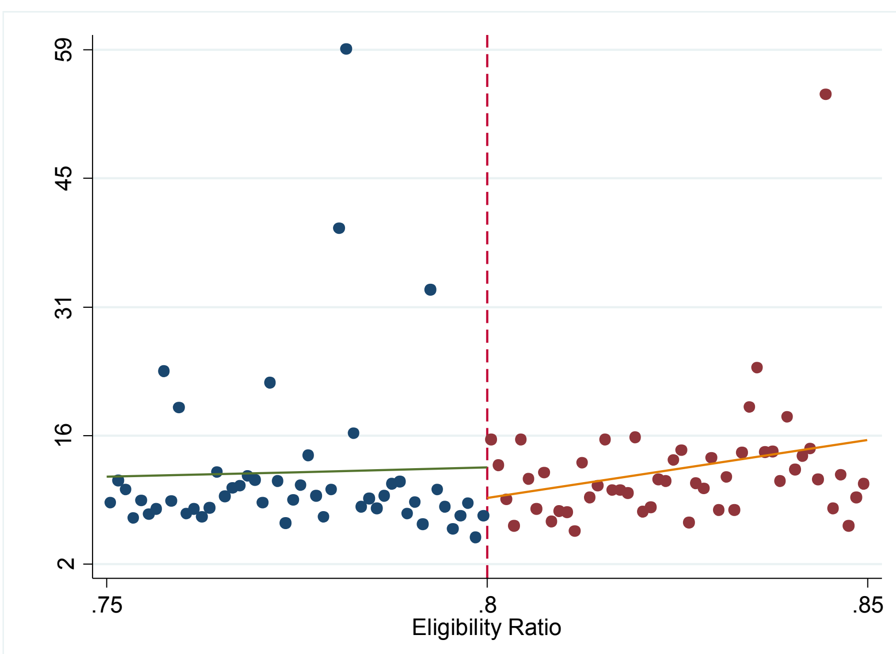
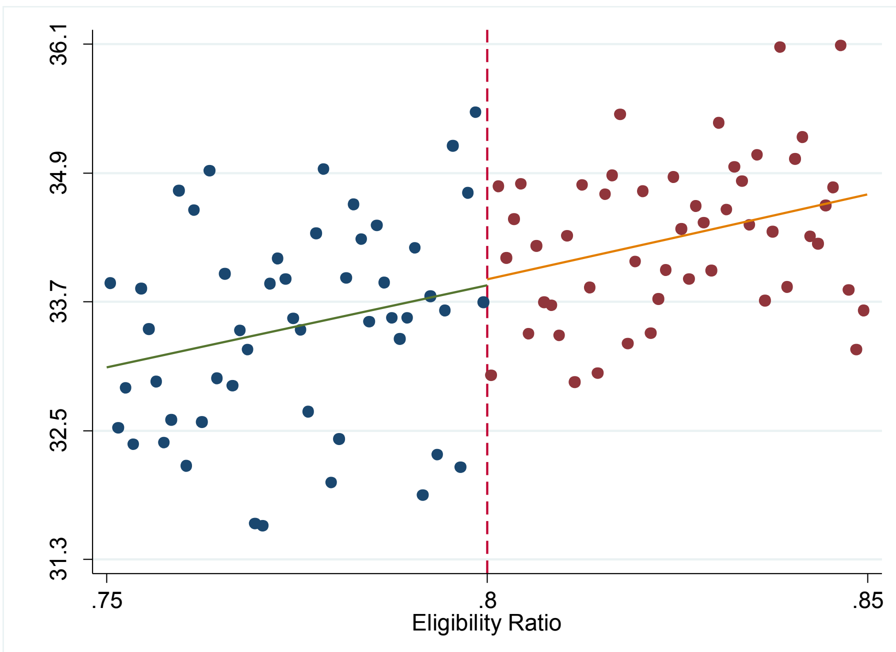


Figure 2.1c: Average Number of New Employment in 2006 over the Eligibility Ratio



To show that there is nothing systematic about this cutoff, we also look at pattern of the average age of a tract, percentage of the tract that is black, percentage of the tract that is Hispanic, and percentage of the tract without a high school diploma. Figures 2.2a through 2.2d show these control variables, respectively, in 2000 across the eligibility ratio. These figures show continuity across the eligibility ratio and suggest that something else going on at this boundary is not driving our results.[32]

Figure 2.2a: Average Age in Census Tract in 2000 over the Eligibility Ratio



[32] Although there is a small jump when crossing the eligibility ratio in the percentage of the tract that is black, the jump after eligibility is an increase in the percentage black. Typically, lower income areas tend to have higher percentage minority. This increase in percentage black acts in the opposite direction of the NMTC and thus is unlikely to bias our results.

Figure 2.2b: Average Percent Black in Census Tract in 2000 over the Eligibility Ratio

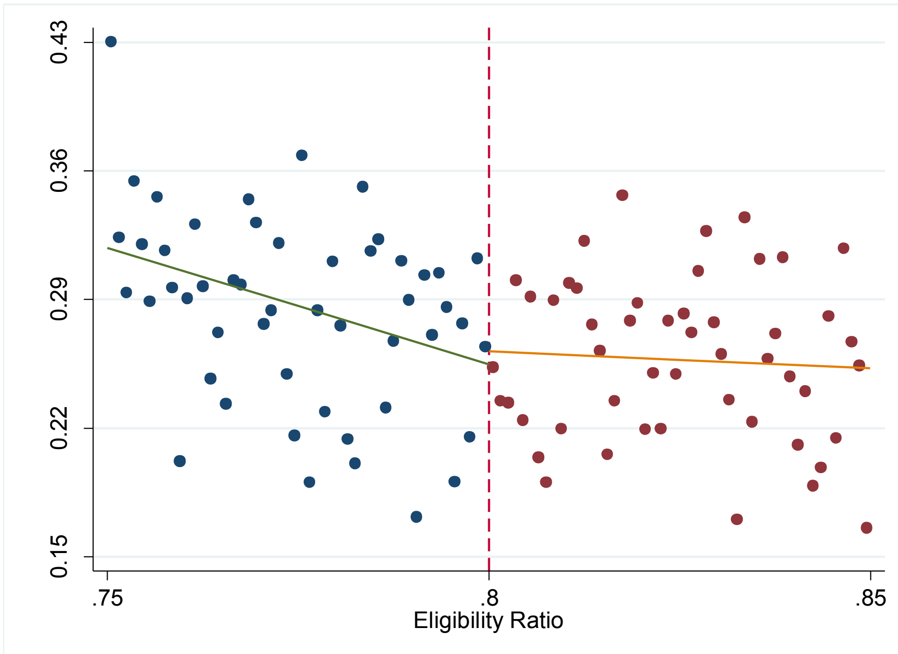


Figure 2.2c: Average Percent Hispanic in Census Tract in 2000 over the Eligibility Ratio

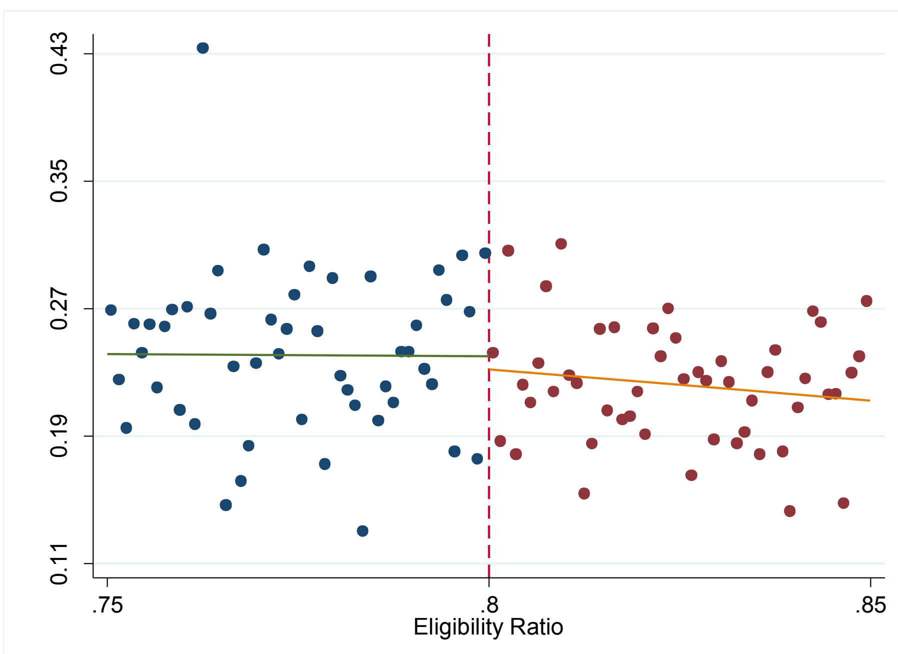
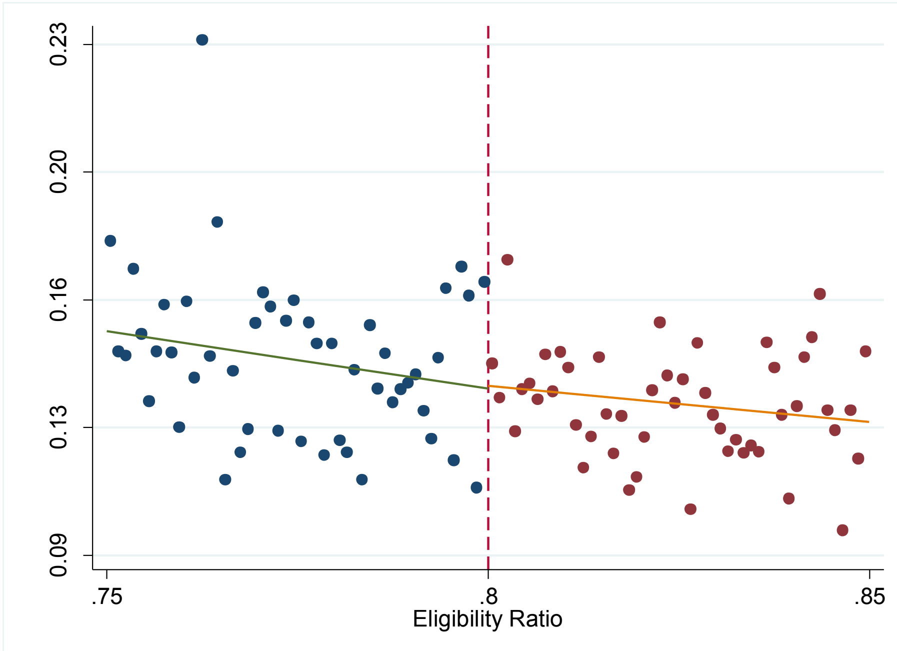


Figure 2.2d: Average Percent No High School Education in Census Tract in 2000 over Eligibility Ratio



2.4 Data

We use two primary data sets for our analysis. First, we use 2000 Census data to control for the local attributes of each tract. Because eligibility for the NMTC was determined in 2000, we use the 2000 decennial census to create our eligibility ratio. Table 2.2a presents the year 2000 summary statistics for tracts that were eligible to receive the NMTC as well as those that were ineligible. As we can see, these two groups are substantially different across many observable characteristics. Those tracts that are eligible for the tax credit tend to have significantly higher unemployment rates, higher percentage of the tract that is black and Hispanic, lower average income, and lower educational levels. Therefore, looking at the entire sample of tracts that are eligible versus those that are not is likely to produce biased estimates, as there are likely to be unobservable attributes of the neighborhoods that may affect the decisions of business owners.

Table 2.2a: 2000 Census Tract Summary Statistics

	Eligible Tracts		Ineligible Tracts	
	Mean	Std. Dev.	Mean	Std. Dev.
Percent Female	51.00%	0.060	51.00%	0.035
Percent Black	26.97%	0.324	8.39%	0.157
Percent Hispanic	18.87%	0.265	8.24%	0.131
Average Age	34.47	5.581	37.00	4.671
Percent Some HS	20.31%	0.078	10.51%	0.059
Percent HS Graduate	33.06%	0.098	29.97%	0.112
Percent Some College	19.49%	0.073	23.44%	0.064
Percent College Graduate	12.68%	0.104	30.38%	0.182
Tract Average Income	39,547	9,354	73,149	3,329
Percent Unemployed	10.60%	0.079	4.57%	0.035

To address this concern regarding unobservable local attributes, we utilize a regression discontinuity research design. We compare tracts that are just above the 0.80 income eligibility ratio to those that are just below the cutoff. In Table 2.2b, we compare those tracts that have a ratio of 0.70 to 0.80 and those tracts with a ratio of 0.80 to 0.90. As shown in this table, these tracts are more similar in terms of the observable attributes than the full sample, suggesting that by focusing on tracts near the income eligibility ratio boundary, we are better able to control for unobserved local attributes.

Table 2.2b: 2000 Census Tract Summary Statistics by ER Range

	Ratio between 0.70 and 0.80		Ratio between 0.80 and 0.90	
	Mean	Std. Dev.	Mean	Std. Dev.
Percent Female	50.90%	0.041	50.97%	0.034
Percent Black	16.66%	0.247	11.20%	0.191
Percent Hispanic	12.87%	0.207	12.27%	0.187
Average Age	36.20	4.848	36.82	4.647
Percent Some HS	17.17%	0.059	15.01%	0.053
Percent HS Graduate	36.06%	0.091	35.97%	0.091
Percent Some College	21.29%	0.066	22.35%	0.062
Percent College Graduate	14.49%	0.091	17.38%	0.099
Tract Average Income	45,245	7,214	51,104	8,027
Percent Unemployed	7.42%	0.042	6.18%	0.037

The second data set used is the Dun and Bradstreet (D&B) Marketplace files for the second quarter of 2002, 2004, and 2006.[33] This data is collected by Dun and Bradstreet and was obtained aggregated to the ZIP code level. We convert the ZIP code level data to year 2000 census tract geography using GIS software.[34] We transform the D&B data to the tract level because census tract median income is the criteria used to determine eligibility for the NMTC program.[35] The D&B data contains a wealth of information on businesses. This includes detailed information on the industry to which each establishment belongs (based on the establishment's Standard Industrial Code), the number of employees, how long the business has been in operation, and sales information.

[33] The D&B data includes nearly all establishments apart from part-time schedule-C filers. The data have been used in a number of studies including Rosenthal and Strange (2001, 2003, 2005) and Rosenthal and Ross (2010). Kolko and Neumark (2010) and Kolko (2012) use a panel version of the data, the National Establishment Time-Series (NETS), that was jointly developed by Don Walls and Dun and Bradstreet.

[34] To make such a conversion, we assume that the businesses within a ZIP code are uniformly distributed throughout the area. Note that in MSAs, only 40 percent of tracts overlap more than one ZIP code.

[35] One concern with this correspondence is that we are creating measurement error by assuming that business activity is distributed uniformly throughout the ZIP code. Based on the distribution of businesses near the cutoff, which are the focus of our analysis, and simulations based on where in the narrow band widths these tracts that cross multiple ZIP codes are located, any bias from this assumption would bias our results towards zero. This suggests that the estimates provided are a lower bound of the effect of the policy. For further information on the distribution of activity across ZIP codes and census tracts, please contact the authors.

Table 2.3a provides summary statistics of new and existing business activity in 2002 in all eligible tracts versus all ineligible tracts. The first two rows contain the mean and standard deviation for businesses in all industries, then we stratify the new and existing businesses by industry type – construction, manufacturing, transportation wholesale, retail, FIRE (financial, insurance, real estate), and services. As we can see, the tracts that are not eligible for the NMTC have more business activity in general than those that are eligible across all industries, as well as for each specific industry.

Table 2.3a: 2002 Business Summary Statistics

	Eligible Tracts		Ineligible Tracts	
	Mean	Std. Dev.	Mean	Std. Dev.
All New Businesses	2.696	5.337	5.2611	7.032
All Existing Businesses	126.484	237.100	217.290	253.26
New Construction	0.276	0.620	0.615	1.013
Existing Construction	9.762	20.315	21.332	26.697
New Manufacturing	0.179	0.550	0.346	0.618
Existing Manufacturing	7.286	19.867	12.236	19.609
New Transportation	0.122	0.348	0.207	0.409
Existing Transportation	4.513	10.654	6.926	10.301
New Wholesale	0.153	0.539	0.270	0.554
Exiting Wholesale	7.752	26.676	12.454	22.616
New Retail	0.648	1.085	1.103	1.475
Existing Retail	27.851	38.889	43.455	45.584
New FIRE	0.168	0.472	0.386	0.702
Existing FIRE	10.850	27.825	20.459	29.641
New Services	1.091	2.383	2.200	2.132
Existing Services	56.630	105.411	96.070	113.977

Just like with Table 2.2b, in Table 2.3b we restrict our sample to those tracts with an income eligibility ratio between 0.70 and 0.90. When we restrict our sample to just those tracts that are slightly above the income eligibility cutoff to those that are slightly below the cutoff, we see that these tracts are more similar regarding the number of new and existing businesses prior to the allocation of the NMTC. The pattern is consistent when we consider all industries, as well as when we focus on each industry separately.

Table 2.3b: 2002 Business Summary Statistics by ER Range

	Ratio between 0.70 and 0.80		Ratio between 0.80 and 0.90	
	Mean	Std. Dev.	Mean	Std. Dev.
All New Businesses	3.135	5.113	3.710	5.098
All Existing Businesses	145.104	190.498	170.422	187.841
New Construction	0.371	0.701	0.452	0.829
Existing Construction	13.102	17.845	16.552	20.053
New Manufacturing	0.212	0.521	0.252	0.475
Existing Manufacturing	8.521	15.651	9.943	13.865
New Transportation	0.149	0.371	0.168	0.343
Existing Transportation	5.363	10.306	6.062	8.018
New Wholesale	0.169	0.555	0.184	0.433
Exiting Wholesale	8.508	22.372	9.491	15.826
New Retail	0.750	1.069	0.886	1.226
Existing Retail	32.307	35.107	37.830	40.066
New FIRE	0.183	0.417	0.219	0.448
Existing FIRE	12.260	20.405	14.552	18.756
New Services	1.221	2.332	1.448	2.113
Existing Services	62.388	81.489	72.630	90.947

Overall, the summary statistics in Tables 2.2a and 2.3a suggest that comparing all eligible tracts to all ineligible tracts is likely to be confounded by unobservable attributes. When we restrict our sample to those tracts just above and just below the eligibility ratio, as we do in Tables 2.2b and 2.3b, we have a set of census tracts that are similar in terms of observable attributes and are more likely to be more comparable to one another.

2.5 Results

Impact of the NMTC on New Employment and Businesses

We begin by looking at the impact of eligibility for the NMTC on new business activity.

Throughout this discussion, we define a new business as an establishment that has been open for less than one year. As mentioned earlier, we do not have information on whether or not a specific business received the tax credit. Therefore, we only use whether or not a tract is eligible for the NMTC as exogenous variation in where new businesses locate. While the decision of which investment projects receive the tax credit is subject to a political process that may be endogenous, eligibility for the NMTC, which is based on census tract characteristics, is likely to be exogenous to the selection procedure.

We first consider all census tracts located within MSAs in the United States. Results using the change in new employment as the dependent variable are presented in Table 2.4a, while the results using new firms as the dependent variable are in Table 2.4b.[36] Panel A contains the results using 2004 as the post policy change period, the year immediately after the NMTC allocations were first distributed. Panel B provides estimates of the effect of the policy change over a longer period, looking at the change from 2002 to 2006. Standard errors are clustered at the MSA level and are reported in parenthesis under each coefficient. All models include neighborhood controls, as well as fixed effects for the two-digit SIC code and state.[37]

[36] All models have been run without controls, since the assumption of the regression discontinuity is that observable attributes should not affect our results. Results from that analysis are consistent with those reported in the paper but are not presented in the interest of space.

[37] The neighborhood attributes included as controls are percent female, percent black, percent Hispanic, average age, measures of educational attainment, average income, unemployment rate, and the percent of households that have a female head of household and children. All of these variables are at the 2000 census tract level.

Table 2.4a: Effect of New Market Tax Credit Qualification Status on the Change in New Employment in Census Tracts in MSAs

	Entire Sample	Eligibility Ratio 0.70 to 0.90	Eligibility Ratio 0.75 to 0.85
	Panel A: 2002 Q2 to 2004 Q2		
NMTC Qualified	-0.021**	0.051***	0.013
Census Tract	(0.008)	(0.018)	(0.030)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,871,385	898,157	443,444
R-squared	0.000	0.001	0.002
	Panel B: 2002 Q2 to 2006 Q2		
NMTC Qualified	-0.057	0.041	0.066**
Census Tract	(0.045)	(0.042)	(0.033)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,874,040	899,042	443,916
R-squared	0.000	0.001	0.001

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Only tracts located within an MSA are included in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

When we consider all census tracts located within an MSA, we find a negative and statistically significant effect of the NMTC on the number of new businesses and new employment, suggesting that the tax incentive deters businesses from locating in eligible areas. However, as mentioned earlier there are issues regarding unobservable differences between high-income and low-income tracts that are likely to bias the estimates. To address these concerns, we restrict the sample to those tracts located in an MSA that are close to the income eligibility ratio, specifically those with an income eligibility ratio between 0.70 and 0.90 and 0.75 and 0.85.

When we restrict the sample to tracts near the income eligibility cutoff, we find evidence that the NMTC has a positive effect on the number of new firms and new employment in 2004 and 2006.[38] We see consistent positive effects of the policy on new employment, with a point estimate between 0.051 and 0.066 percentage points, though we only have statistical significance when the eligibility ratio is between 0.70 and 0.90 in 2004 and between 0.75 and 0.85 in 2006. Overall, our results suggest that the NMTC increased new employment in those areas close to the income eligibility ratio.

Table 2.4b contains our results regarding the effect of the NMTC on the number of new firms in eligible tracts. As was the case with employment, we find the negative effect for the entire sample, but this is not surprising given the likelihood that we have unobserved variables present when considering all tracts. When we focus on those areas close to the boundary, we find positive and statistically significant increases in the number of new firms of between 0.007 and 0.009 percentage points within 0.70 and 0.90 of the income eligibility ratio. However, when we look closer to the cutoff at 0.75 to 0.85, we have similar coefficients but the standard errors have increased so we no longer obtain statistically significant effects. Overall, our findings suggest that the policy had a positive impact on those census tracts that are close to the 0.80 income eligibility ratio cutoff.

[38] One concern is that the 2000 decade had a decline in business activity, followed by a period of growth, which then turned into a recession late in the decade. Given our identification strategy, we are comparing tracts that are eligible for the tax credit to those that are not eligible for the tax credit in a given year. Therefore, as long as any shocks to the economy affect the tracts in our sample in a similar manner, then business cycle trends will not bias our estimates. While this is likely to be a concern when looking at all census tracts, it is less likely this is driving our results when we are comparing those tracts that are just eligible to those that are just ineligible.

Table 2.4b: Effect of New Market Tax Credit Qualification Status on the Change in New Firms in Census Tracts in MSAs

	Entire Sample	Eligibility Ratio 0.70 to 0.90	Eligibility Ratio 0.75 to 0.85
	Panel A: 2002 Q2 to 2004 Q2		
NMTC Qualified	-0.006***	0.007***	0.007
Census Tract	(0.001)	(0.002)	(0.005)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,871,385	898,157	443,444
R-squared	0.095	0.059	0.063
	Panel B: 2002 Q2 to 2006 Q2		
NMTC Qualified	-0.009***	0.009***	0.008
Census Tract	(0.001)	(0.002)	(0.006)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,874,040	899,042	443,916
R-squared	0.101	0.078	0.085

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Only tracts located within an MSA are included in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Impact of the NMTC by Industry

Next, we consider how the effect of the tax credit varies across different industries. As noted above, the NMTC was used primarily for capital investments, such as office renovations and real estate. As shown previously by Hanson and Rohlin (2013) and Patrick (2014), taxes and subsidies do not necessarily have the same effect across all industries. In addition, McCulloch and Yellen (1977) suggest that capital tax credits may have perverse labor market effects, as the programs may incentivize firms to replace low-skilled workers with capital that has now become relatively less expensive. Therefore, we look next at how the effect of the policy varies both across new employment and firm openings across industries.

Looking first at the effect on employment at new firms located in census tracts with an eligibility ratio between 0.70 and 0.90 in Table 2.5a, we find positive and statistically significant employment effects in both 2004 and 2006 for FIRE and services. The magnitude of this increase is approximately 0.04 percentage points for FIRE and 0.13 percentage points for services. Given that a large portion of the funds allocated through the NMTC went towards office space and real estate, the positive effect on FIRE is expected.[39] In addition, services includes educational and social services. As mentioned earlier, this is one of the primary areas that the NMTC was allocated towards, so this positive effect is consistent with how the tax credit allocations were used. When we look at areas within 0.75 and 0.85 of the eligibility ratio in Table 2.5b, we still find a positive effect of a similar magnitude of the NMTC on employment in services and FIRE. These results indicate that the overall positive effect we find on employment seems to be driven primarily by FIRE and services.

[39] Note that the "real estate" in FIRE references real estate firms. We would expect that if investment in real estate increased, that there would be positive effects on these types of businesses. However, it should be noted that this does not necessarily mean that is where the real estate investment took place. For example, a manufacturing firm could use the tax credit to buy additional land to expand their operations, but this type of investment would directly affect manufacturing firms.

Table 2.5a: Effect of New Market Tax Credit Qualification Status on the Change in New Employment in a Census Tract with an Eligibility Ratio between 0.70 and 0.90 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 2002 Q2 to 2004 Q2				
NMTC Qualified	0.108*	0.005	0.017	0.065	0.045**	0.035*	0.128***
Census Tract	(0.061)	(0.022)	(0.034)	(0.044)	(0.017)	(0.019)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,669	304,460	60,892	30,446	121,784	106,561	213,122
R-squared	0.008	0.001	0.001	0.002	0.001	0.001	0.004
			Panel B: 2002 Q2 to 2006 Q2				
NMTC Qualified	0.044	-0.014	0.026	-0.006	0.023	0.038*	0.140*
Census Tract	(0.034)	(0.107)	(0.016)	(0.066)	(0.015)	(0.023)	(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,714	304,760	60,952	30,476	121,904	106,666	213,332
R-squared	0.021	0.001	0.002	0.003	0.001	0.001	0.001

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Table 2.5b: Effect of New Market Tax Credit Qualification Status on the Change in New Employment in a Census Tract with an Eligibility Ratio between 0.75 and 0.85 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 2002 Q2 to 2004 Q2				
NMTC Qualified	-0.181	-0.033	-0.069	-0.111	0.068*	0.043	0.126*
Census Tract	(0.229)	(0.055)	(0.081)	(0.166)	(0.040)	(0.040)	(0.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,548	150,320	30,064	15,032	60,128	52,612	105,224
R-squared	0.017	0.001	0.001	0.002	0.001	0.002	0.006
			Panel B: 2002 Q2 to 2006 Q2				
NMTC Qualified	0.027	0.045***	0.002	0.105**	0.020	0.036**	0.159
Census Tract	(0.057)	(0.015)	(0.020)	(0.047)	(0.039)	(0.014)	(0.121)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,572	150,480	30,096	15,048	60,192	52,668	105,336
R-squared	0.026	0.001	0.008	0.010	0.002	0.012	0.004

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Tables 2.6a and 2.6b follow the same structure as Tables 2.5a and 2.5b but use the change in the number of new firms as the dependent variable. Across both years and distance bands, we find strong evidence that there is a positive effect of the NMTC on new firms in all industries except for construction and transportation. Combining these results with the employment results, this suggests that firms in manufacturing, wholesale, retail, FIRE, and services were able to use the funds towards capital investment. However, we do not find an increase in the number of establishments leads to an increase in employment in manufacturing, wholesale, and retail. This result is consistent with McCulloch and Yellen (1977) who argued that programs which adjust the relative price of capital and labor may have unintended consequences of causing firms to replace low-skilled workers with capital investments.

Table 2.6a: Effect of New Market Tax Credit Qualification Status on the Change in New Firms in a Census Tract with an Eligibility Ratio between 0.70 and 0.90 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 2002 Q2 to 2004 Q2				
NMTC Qualified	0.012*	0.001**	0.001	0.011**	0.008***	0.004***	0.015***
Census Tract	(0.006)	(0.001)	(0.002)	(0.004)	(0.003)	(0.001)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,669	304,460	60,892	30,446	121,784	106,561	213,122
R-squared	0.066	0.009	0.028	0.024	0.049	0.038	0.058
			Panel B: 2002 Q2 to 2006 Q2				
NMTC Qualified	0.011	0.002***	0.006**	0.014***	0.011***	0.008***	0.017***
Census Tract	(0.009)	(0.001)	(0.003)	(0.004)	(0.004)	(0.002)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,714	304,760	60,952	30,476	121,904	106,666	213,332
R-squared	0.075	0.021	0.030	0.029	0.048	0.049	0.078

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote $p<0.01$, $p<0.05$, and $p<0.1$, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Table 2.6b: Effect of New Market Tax Credit Qualification Status on the Change in **NEW** Firms in a Census Tract with an Eligibility Ratio between 0.75 and 0.85 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
				Panel A: 2002 Q2 to 2004 Q2			
NMTC Qualified	0.012	0.001	-0.001	0.002	0.010*	0.004**	0.017*
Census Tract	(0.014)	(0.001)	(0.007)	(0.017)	(0.005)	(0.002)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,548	150,320	30,064	15,032	60,128	52,612	105,224
R-squared	0.071	0.012	0.034	0.031	0.054	0.043	0.061
				Panel B: 2002 Q2 to 2006 Q2			
NMTC Qualified	0.017	0.003***	0.003	0.014	0.016***	0.004	0.011
Census Tract	(0.018)	(0.001)	(0.008)	(0.010)	(0.006)	(0.005)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,572	150,480	30,096	15,048	60,192	52,668	105,336
R-squared	0.081	0.023	0.040	0.034	0.052	0.055	0.085

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote $p<0.01$, $p<0.05$, and $p<0.1$, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Impact of the NMTC on Existing Employment

Next, we examine the impact of the NMTC on existing employment.[40] The goal of the NMTC was to incentivize investors to allocate more funds in lower income tracts. The credits could be used for either new businesses or existing establishments, where we define an existing business as one that has been open for at least four years.[41] Therefore, it is possible that the NMTC has an effect on existing businesses through increased capital investment in these establishments.[42]

In Table 2.7, we look at the effect of eligibility for the NMTC on existing employment. We see that when considering all census tracts located within MSAs, the effect of the policy is negative, but is not statistically significant. When we focus on just those tracts close to the boundary, we find positive effects, but again we do not find that these effects are statistically significant. This suggests that while the NMTC could have been used towards existing firms, it appears that the credit had the strongest effect on attracting new firms versus affecting the activities of existing establishments.

---

[40] We have also run all these regressions using the number of existing firms. Since we are primarily interested in employment effects, we choose to only show these results to streamline the discussion.

[41] We consider existing firms to be those firms that have been open four or more years, given the high closure rate of young firms. We believe this measure of existing firms captures established firms past the initial failure period.

[42] Another mechanism through which the policy could affect existing businesses is if the tax credit created turnover with regards to existing firms (see Rohlin and Ross (2015) for more information on how policy may create business turnover versus net new businesses).

Table 2.7: Effect of New Market Tax Credit Qualification Status on the Change in Existing Employment in Census Tracts in MSAs

	Entire Sample	Eligibility Ratio 0.70 to 0.90	Eligibility Ratio 0.75 to 0.85
	Panel A: 2002 Q2 to 2004 Q2		
NMTC Qualified	-0.358	0.623	1.889
Census Tract	(0.418)	(1.465)	(1.447)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,948,429	911,834	450,477
R-squared	0.017	0.010	0.015
	Panel B: 2002 Q2 to 2006 Q2		
NMTC Qualified	-0.477	0.867	2.022
Census Tract	(0.408)	(1.292)	(1.376)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,948,429	911,834	450,477
R-squared	0.015	0.009	0.012

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Only tracts located within an MSA are included in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

In Tables 2.8a and 2.8b, we examine the effect of the tax credit by industry. Looking across both tables, we find positive and statistically significant increases in employment in construction, retail, and FIRE. The increase in existing employment in construction is consistent with the capital tax credit leading to new capital investments. If the funds went to capital investments, then firms will likely need to undergo some form of construction, causing employment at construction firms to increase. Retail and FIRE firms also experienced an increase in employment. One explanation for the effect on retail is that retail includes eating and drinking places. Given the increases in employment, there will likely be higher demand for places to have lunch and dinner, causing expansions in employment at these firms. The positive effect on FIRE would similarly be based on increased demand for the services offered by these establishments, especially those involved in real estate.

Table 2.8a: Effect of New Market Tax Credit Qualification Status on the Change in Existing Employment in a Census Tract with an Eligibility Ratio between 0.70 and 0.90 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 2002 Q2 to 2004 Q2				
NMTC Qualified	2.372**	0.165	0.496	0.781	1.401***	-0.274	0.904
Census Tract	(1.125)	(1.544)	(0.701)	(2.175)	(0.513)	(2.360)	(2.303)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,981	306,540	61,308	30,654	122,616	107,289	222,119
R-squared	0.018	0.003	0.005	0.006	0.022	0.003	0.012
			Panel B: 2002 Q2 to 2006 Q2				
NMTC Qualified	2.323**	0.108	0.444	1.391	1.296**	0.855	1.446
Census Tract	(1.065)	(1.577)	(0.674)	(2.071)	(0.596)	(1.376)	(2.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,981	306,540	61,308	30,654	122,616	107,289	222,119
R-squared	0.021	0.003	0.004	0.007	0.015	0.003	0.013

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Table 2.8b: Effect of New Market Tax Credit Qualification Status on the Change in Existing Employment in a Census Tract with an Eligibility Ratio between 0.75 and 0.85 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 2002 Q2 to 2004 Q2				
NMTC Qualified	1.363	1.099	0.675	2.581	2.188**	2.479**	2.992
Census Tract	(3.553)	(0.704)	(0.954)	(3.360)	(1.050)	(1.194)	(3.586)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,716	151,440	30,288	15,144	60,576	53,004	109,737
R-squared	0.030	0.002	0.007	0.010	0.038	0.004	0.023
			Panel B: 2002 Q2 to 2006 Q2				
NMTC Qualified	2.012	1.206**	1.423**	2.299	2.378**	3.284*	2.580
Census Tract	(2.215)	(0.575)	(0.645)	(3.375)	(1.055)	(1.756)	(3.526)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,716	151,440	30,288	15,144	60,576	53,004	109,737
R-squared	0.036	0.002	0.008	0.013	0.016	0.005	0.024

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Eligibility ratio cutoff of 0.75to 0.85 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Using 1994 as the Pre-Policy Change Year

While applications for the NMTC were not accepted until July of 2002, because the legislation was passed in 2000 there may be concerns that 2002 is not the appropriate pre-policy change year. To address this concern, we estimate the effect of the NMTC using 1994 as the pre-policy change year and 2002, 2004, and 2006 as the post-policy change years. Because the D&B survey started in the early 1990s, there were some issues initially regarding the employment numbers.[43] For that reason, we focus on the effect of the NMTC on new establishments.

Table 2.9 presents the results of the impact of the NMTC on the change in new firms using 1994 as the base year. We find the same negative and statistically significant effect across all tracts, consistent with the selection issue we have argued is present throughout the paper. We find a positive and statistically significant effect when we only consider those tracts between 0.70 and 0.90 of the eligibility ratio, consistent with the results earlier in the paper. We continue to find a positive effect when we restrict the sample to be even closer to the boundary at 0.75 and 0.85, but the standard errors increase and we no long have statistical significance.

[43] In 1994, there were 831 tracts that reported having at least one new firm but no new employees at those firms. In 2002, there were no tracts with this reporting problem, and in 2004 and 2006 there were 3 and 4 respectively. For this reason, we are not confident in the employment numbers in 1994, and therefore focus on the firm results.

Table 2.9: Effect of New Market Tax Credit Qualification Status on the Change in New Firms in Census Tracts in MSAs using 1994 as Base Year

	Entire Sample	Eligibility Ratio 0.70 to 0.90	Eligibility Ratio 0.75 to 0.85
	Panel A: 1994 Q2 to 2002 Q2		
NMTC Qualified	-0.012***	0.010**	0.010
Census Tract	(0.003)	(0.004)	(0.010)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	3,009,944	459,138	226,619
R-squared	0.133	0.078	0.076
	Panel B: 1994 Q2 to 2004 Q2		
NMTC Qualified	-0.006***	0.004**	0.003
Census Tract	(0.001)	(0.002)	(0.005)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,871,385	898,157	443,444
R-squared	0.054	0.029	0.032
	Panel C: 1994 Q2 to 2006 Q2		
NMTC Qualified	-0.009***	0.006***	0.004
Census Tract	(0.001)	(0.002)	(0.006)
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	5,874,040	899,042	443,916
R-squared	0.061	0.042	0.048

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Only tracts located within an MSA are included in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

When we consider the results across industries, we still find strong positive effects in FIRE and services in the 0.70 to 0.90 band, as is shown in Table 2.10a. In Table 2.10b, when we look even closer to the boundary near 0.75 and 0.85, we find evidence that the coefficients tend to be positive, but do not obtain statistical significance in almost all of the regressions. Overall, our findings using 1994 as the pre-period year are consistent with the findings presented earlier in the paper using 2002 as the pre-policy change year.

Table 2.10a: Effect of New Market Tax Credit Qualification Status on the Change in New Firms in a Census Tract with an Eligibility Ratio between 0.70 and 0.90 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
Panel A: 1994 Q2 to 2002 Q2							
NMTC Qualified	0.021	0.002	0.002	0.003	0.005	0.008***	0.027***
Census Tract	(0.017)	(0.001)	(0.004)	(0.009)	(0.007)	(0.003)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,346	155,640	31,128	15,564	62,256	54,474	108,948
R-squared	0.114	0.009	0.045	0.017	0.079	0.039	0.081
Panel B: 1994 Q2 to 2004 Q2							
NMTC Qualified	0.013*	0.00003	-0.001	-0.0002	0.0012	0.003***	0.012***
Census Tract	(0.007)	(0.0004)	(0.002)	(0.005)	(0.003)	(0.001)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,669	304,460	60,892	30,446	121,784	106,561	213,122
R-squared	0.032	0.002	0.010	0.003	0.009	0.015	0.037
Panel C: 1994 Q2 to 2006 Q2							
NMTC Qualified	0.012	0.001	0.005*	0.004	0.003	0.008***	0.014***
Census Tract	(0.009)	(0.001)	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,714	304,760	60,952	30,476	121,904	106,666	213,332
R-squared	0.043	0.006	0.018	0.003	0.014	0.028	0.052

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote $p<0.01$, $p<0.05$, and $p<0.1$, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

Table 2.10b: Effect of New Market Tax Credit Qualification Status on the Change in New Firms in a Census Tract with an Eligibility Ratio between 0.75 and 0.85 Classified by Industry.

	Constr	Manufact	Transport	Wholesale	Retail	FIRE	Services
			Panel A: 1994 Q2 to 2002 Q2				
NMTC Qualified	0.021	0.002	0.003	0.014	0.007	0.006	0.024
Census Tract	(0.026)	(0.002)	(0.009)	(0.016)	(0.014)	(0.005)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,523	76,820	15,364	7,682	30,728	26,887	53,774
R-squared	0.115	0.011	0.054	0.023	0.080	0.041	0.078
			Panel B: 1994 Q2 to 2004 Q2				
NMTC Qualified	0.011	-0.0003	-0.003	-0.007	0.001	0.001	0.012
Census Tract	(0.012)	(0.001)	(0.007)	(0.015)	(0.005)	(0.002)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,548	150,320	30,064	15,032	60,128	52,612	105,224
R-squared	0.038	0.003	0.017	0.005	0.010	0.018	0.040
			Panel C: 1994 Q2 to 2006 Q2				
NMTC Qualified	0.016	0.002***	0.001	0.005	0.007	0.002	0.006
Census Tract	(0.016)	(0.001)	(0.008)	(0.006)	(0.004)	(0.005)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,572	150,480	30,096	15,048	60,192	52,668	105,336
R-squared	0.051	0.009	0.026	0.005	0.016	0.034	0.059

Standard errors are clustered at the MSA level and are reported in parentheses. ***, **, and * denote p<0.01, p<0.05, and p<0.1, respectively. Eligibility ratio cutoff of 0.70 to 0.90 included in all columns in this table. State and industry fixed effects are included in the regressions. Control variables include the percent of the population that is female, the percent of the population that is black, the percent of the population that is Hispanic, the average age of the population, the percent of the population without a high school diploma, the percent of the population with some college, the percent of the population with a college degree, the average income, the unemployment rate, and the percent of female headed households with children within the tract.

2.6 Conclusions and Policy Implications

In this paper, we examine the effect of the New Markets Tax Credit on new businesses and employment levels at these new establishments. However, there are selection issues that must be addressed when considering the effect of the policy on local jurisdictions. First, when firms choose where to open their new enterprise, as there are likely to be unobservable attributes of the neighborhood affecting this decision. Second, not all firms that applied for the NMTC received the credit, so there may be issues regarding which firms are selected for the program. To address these concerns, we use a regression discontinuity design and a differencing strategy to compare census tracts just on either side of a plausibly exogenous eligibility ratio. By utilizing this exogenous cutoff, we obtain causal estimates of the effect of the NMTC on the location decisions of new businesses.

When we focus on tracts located in MSAs near the income eligibility ratio, we find that NMTC eligibility attracts new businesses and new employment to these areas in 2004 and 2006. When we stratify our results by industry, we find the effects on new employment are most concentrated in services and FIRE. This is consistent with expectations, given that tax credits were primarily allocated towards real estate and social, health, and educational services. We find positive effects on the number of new establishments across all industries, except for construction and transportation. Taken together, this suggests that the policy allowed new firms to open in eligible areas, but there were limited employment effects across industries.

The goal of the NMTC was to increase investment in struggling areas, with the hope that this investment will attract more businesses and spur growth. While we do find increases in the total number of new firms in most industries, we do not find the same consistent effect when we focus on employment. This is consistent with the research of McCulloch and Yellen (1977) which suggested that capital subsidies may have perverse effects on businesses. In particular, our research supports their claim that capital subsidies will cause firms to reallocate resources towards capital investments versus hiring low-skilled workers. However, it should be noted that our findings are only applicable to those tracts that are close to the 0.80 eligibility ratio cutoff and cannot necessarily be generalized to tracts that are not near this boundary. Also, given data limitations we are only able to estimate the short-term effects of the policy. Future research should consider the long-run effects of the program, as it is important to know if these employment effects that we found have lasting effects on these areas.

It should also be noted that there are possible spillover and sorting effects present, as firms may choose to relocate from one area that is ineligible to another area that is eligible for the tax credit. Unfortunately, given the nature of our data we cannot measure these spillovers and movements of firms. Future work should consider the spillover effects of the program on different areas and determine if these tax credits are simply causing firms to move from one area to another or if new business activity is being created through the policy.

Chapter 3
Bad Ink: Visible Tattoos and Recidivism

3.1 Introduction

In 2011, over 600,000 inmates were released from prison (Carson and Sabol, 2011). This large influx of ex-offenders into American communities translates into large populations of individuals attempting to reenter the labor force. Ex-offenders are particularly important labor force participants because research suggests that employment post-release is important for reducing the likelihood of criminal activity and incarceration in the future[44]. In additional to their criminal record, educational background, lack of sills, and personal appearance all limit an ex-offender's propensity to obtain employment post-release. However few studies focus on the impact of personal appearance on the likelihood of obtaining employment post-release from prison (Freeman, 2003). Visible tattoos are one specific aspect of an individual's personal appearance that may affect their likelihood of gaining employment.

Conventional wisdom suggests that individuals with tattoos visible in the workplace may have fewer employment opportunities than people with similar qualifications and no visible tattoos. Visible tattoos may create even more of an employment barrier for the ex-offender population because potential employers may interpret the tattoos (correctly or incorrectly) as signals of criminality. Research on criminal signaling mechanisms details how some criminals use tattoos as a visual résumé for their prior criminal acts (Gambetta, 2009). If employers are aware that tattoos are used to signal criminality, then while interviewing potential employees

[44] Several articles citing anecdotal evidence argue that small-scale reentry programs emphasizing fast employment post-release successfully reduce recidivism rates of program participants compared to similar individuals recently released from prison that do not participate in work-first programs. For an overview of the literature on small-scale reentry programs whose primary focus is on obtaining employment quickly after release please see Freeman, 2003; Tahmincioglu, 2010; Husock, 2012; Pia Negro, 2012; Rosenberg, 2012.

from a pool of ex-offenders, non-tattooed or non-visibly tattooed ex-offenders may seem more reformed than ex-offenders with visible tattoos. In this paper, I examine whether inmates with visible tattoos return to incarceration faster than non-tattooed inmates.

Two recent criminology studies also attempt to estimate the relationship between visible tattoos and recidivism. Lozano et al. (2010) consider a small sample of inmates with prison tattoos, inmates with non-prison tattoos, and college students. The results from their study suggest that inmates with prison tattoos score higher on recidivism risk assessments than inmates without prison tattoos and college students. Waters (2012) expands upon Lozano et al. (2010) using data from the FDOC and examines the relationship between visible tattoos and the occurrence of recidivism within the last three years. The results suggest that inmates with visible tattoos are more likely to be reconvicted for new felony offenses and new violent offenses within three years.

Although these studies take a first step at linking tattoos to recidivism, both have important limitations. Lozano et al. (2010) use a sample of 274 inmates and college students and examine the correlations between tattoo and criminal history variables. It is possible that the relationships found within their data are a function of this small sample size. Additionally, no regression analysis is used within their study, so they are unable to control for other factors related to recidivism. Waters (2012) builds on the work by Lozano et al. (2010) using logistic regressions to examine the likelihood of recidivism for inmates based on tattoo visibility. However, Waters (2012) considers only whether or not an inmate returned to prison, and fails to account for the timing of recidivism within the three year follow-up period. In that case, an inmate who returns to prison on the last day of the three year period he considers is treated identically to an inmate who returns to prison on the first day post-release.

In order to account for the differences in timing of recidivism, I use a log-logistic survival model to examine the relationship between visible tattoos and length of time until reincarceration. The dependent variable in this survival model contains two-parts, whether or not an inmate was reincarcerated, and the length of time until the re-incarceration. Previous work identifies the use of hazard or survival analysis to analyze recidivism as the preferred approach, as it accounts for both the timing and occurrence of re-offense (Baumer, 1997). I use data from the Florida Department of Corrections (FDOC) Offender Based Information System (OBIS) database, which provides demographic, criminal history, and tattoo description information on all inmates released from FDOC facilities during 2008, 2009, and 2010.

One of the issues with estimating differences in recidivism of non-tattooed and tattooed inmates is potential self-selection into receiving a tattoo. Perhaps tattoos signal unobservable characteristics about individuals, which are correlated with factors related to the propensity to commit crimes and return to prison. To attempt to mitigate some of these selection issues, I compare the effects of tattoos within tattooed-subsamples of the prison population. First, I examine the effect of having a visible tattoo on recidivism, within the subsample of tattooed inmates. Next, I limit the sample even further to the subsample of *visibly* tattooed inmates. When considering all inmates who have self-selected into getting a visible tattoo, I isolate the effect of a tattoo located on the head, face, neck, or hands of an ex-offender. Although this process does not provide causal estimates, limiting the sample helps to eliminate some of the selection effects initially present.

I make three significant contributions to the literature on inmate tattoos and recidivism. First, I examine the largest sample considered thus far in the literature, 97,156 inmates, which provides the criminal history of all inmates exiting FDOC facilities over 2008, 2009, and 2010.

This dataset provides a complete picture of the population of inmates released from Florida prisons over three years and with a follow-up period of three years from their release. Second, I develop two classifications of tattoo visibility whereas only one previous study takes into account visibility and defines it as a tattoo located on the arms, hands, neck, or face of an individual (Waters, 2012). Whether or not a tattoo is visible in the workplace is dependent on the type of work environment in question and use of multiple measures of visibility sheds light on which tattoo locations matter most for employment. Finally, I extend previous work on tattoos and reoffense using the survival methodology suggested within the literature as the appropriate approach to examining recidivism.

The remainder of this paper progresses as follows. Section 3.2 describes the FDOC OBIS data. Sections 3.3 explains the methodology used to estimate the survival length of inmates in society before returning to prison. Section 3.4 presents the results and section 3.5 concludes.

3.2 Data

The Florida Department of Corrections (FDOC) Offender Based Information System (OBIS) database includes inmate-level data on all individuals incarcerated within or released from FDOC facilities between October 1997 and October 2013. [45] For each inmate the database documents demographic information, criminal history record within Florida prisons, and descriptions of tattoos and their locations.

[45] The FDOC began recording *all* receipts and releases from FDOC facilities in October 1997 and thus data post-1997 is complete, containing all inmates from that time period, whereas data on incarcerations pre-1997 is only included for inmates who returned to incarceration post-1997. For example, if an inmate was incarcerated in 1998 and was also previously incarcerated in an FDOC facility in 1960, that inmate's criminal history includes both the 1960 incarceration and the 1998 incarceration. However, if an individual served time in a FDOC facility during 1960 and did not recidivate post-1997, they do not appear within the FDOC OBIS database. Therefore, I only consider information on inmates incarcerated after 1997 due to these sample issues.

The focus of this analysis is whether tattoo visibility affects recidivism. Previous research defines a tattoo as visible if located on the arms, hands, neck, or face of an individual (Waters, 2012). Although this definition clearly captures visibility, whether or not a tattoo is visible is dependent on workplace attire in the occupation. As such, additional tests to examine different levels of visibility help to clarify if tattoos in some locations affect recidivism more than others. Furthermore, employers may interpret tattoos in different locations in different ways, especially as some tattoos become more common over time. It is possible that arm and leg tattoos are popular enough in the general population that employers' decisions are not affected by the existence of a visible tattoo of this type. However, if face and neck tattoos are not as popular in the general population, then employers' decisions may still reflect signals sent by these tattoos. The use of multiple visibility classifications allows for the examination of those differences.

The unique data from FDOC allows for two classifications of visibility to be tested. The first classification, visible_1, considers tattoos on the face, head, neck, and hands as visible. Visible_1 represents tattoos visible if a suit or long sleeves and pants are worn each day in the workplace. Table 3.1a presents summary statistics on the entire sample of inmates used within this analysis. Roughly 22% of ex-offenders within my sample have tattoos on their face, head, neck, or hands. Figure 3.1 depicts the visible_1 classification visually. A less stringent classification, visible_2, classifies visible tattoos as those appearing on the face, head, neck, hands, arms, or legs. The second visibility classification represents tattoos visible if an individual is wearing a t-shirt and shorts. Roughly 63% of inmates within my sample have tattoos located on the face, head, neck, hands, arms, or legs. The visible_2 classification is represented visually in figure 3.2. Exploiting different levels of tattoo visibility also allows for a robustness check to ensure that my classification of visibility is not driving the results.

Table 3.1a: Summary Statistics for Entire Sample.					
Variable	Observations	Mean	St. Dev.	Min	Max
Survival Indicators					
Failure	97156	0.221	0.415	0	1
Days until recidivism	97156	974	266	0	1095
Tattoo Indicators					
Tattoo	97156	0.694	0.461	0	1
Visible_1	97156	0.216	0.412	0	1
Visible_2	97156	0.634	0.482	0	1
Demographic Controls					
Black	97156	0.461	0.499	0	1
Asian/Pacific Islander	97156	0.0001	0.011	0	1
Hispanic	97156	0.036	0.186	0	1
White	97156	0.500	0.500	0	1
American Indian	97156	0.0009	0.030	0	1
Age at release	97156	36	11	15	88
Gender	97156	0.882	0.323	0	1
Criminal Controls					
Violent offense in history	96907	0.218	0.413	0	1
Property offense in history	96907	0.349	0.477	0	1
Length of last incarceration	95756	1383	10856	365	367745
Number of previous incarcerations	97156	2	2	1	16

Table 3.1b: Summary Statistics for Tattooed Subsample**.**						
	Visible_1		Visible_2		Non-Visible Tattooed	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Survival Indicators						
Failure	0.351	0.477	0.267	0.442	0.165	0.371
Days until recidivism	907	308	951	283	1003	242
Demographic Controls						
Black	0.447	0.497	0.457	0.498	0.320	0.466
Asian/Pacific Islander	0.000	0.010	0.000	0.009	0.000	0.019
Hispanic	0.044	0.204	0.036	0.186	0.040	0.196
White	0.506	0.500	0.504	0.500	0.637	0.481
American Indian	0.001	0.037	0.001	0.031	0.001	0.032
Age at release	30	8	33	9	36	10
Gender	0.877	0.328	0.900	0.300	0.740	0.439
Criminal Controls						
Violent offense in history	0.213	0.409	0.224	0.417	0.166	0.373
Property offense in history	0.394	0.489	0.372	0.483	0.317	0.465
Length of last incarceration	981	5146	1060	5017	1126	6919
Number of previous incarcerations	2	2	2	2	2	2

Figure 3.1: Diagram of Areas Comprising the Visible_1 Classification.

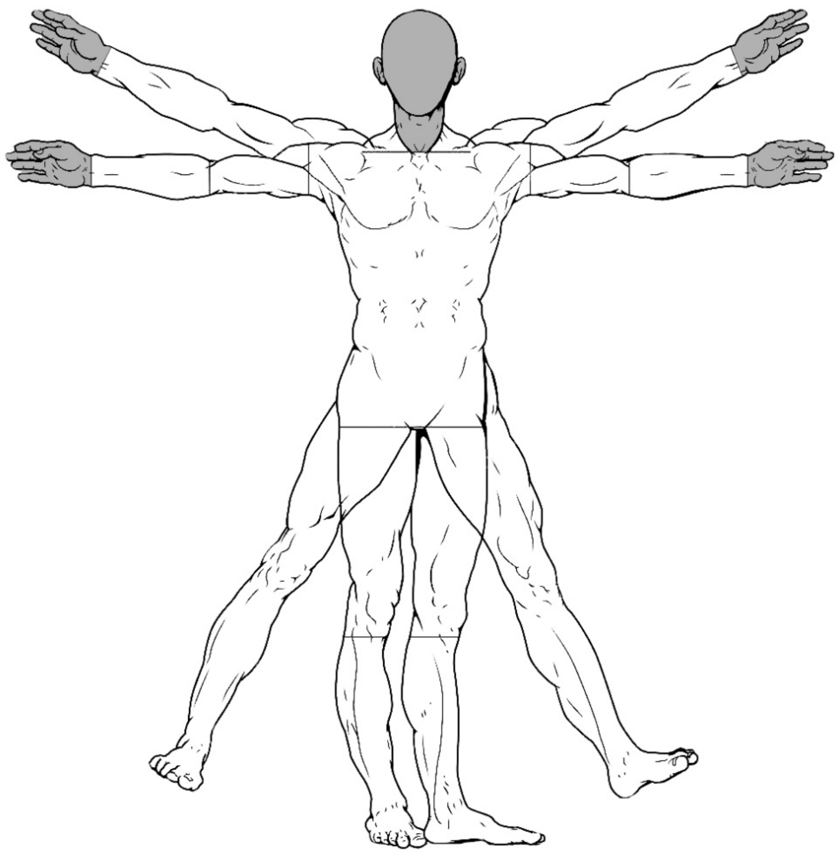
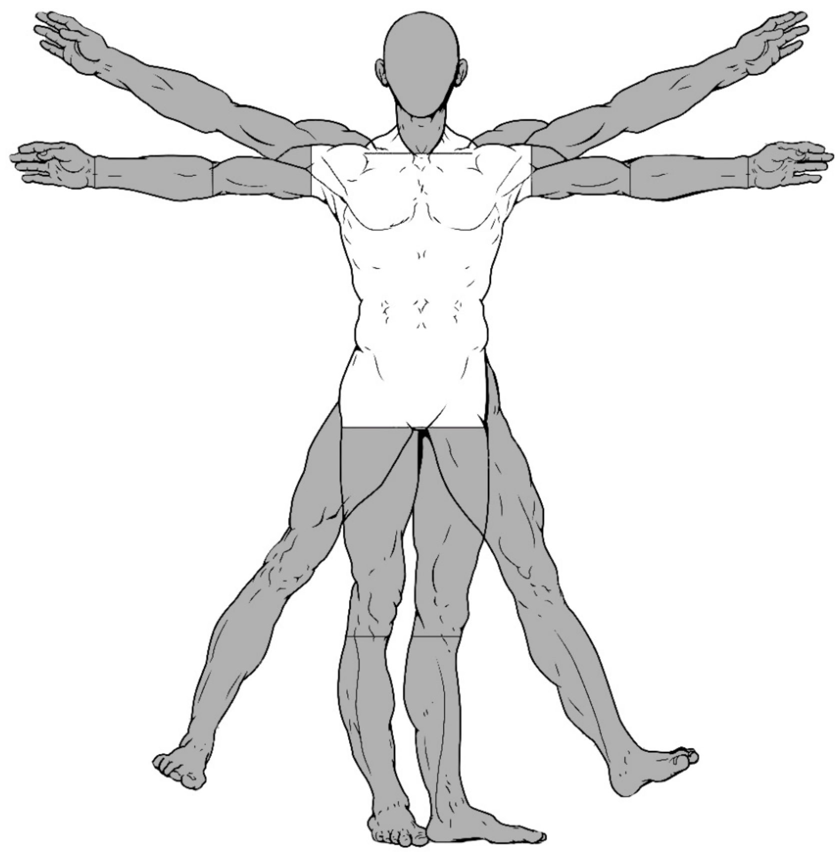


Figure 3.2: Diagram of Areas Comprising the Visible_2 Classification.



Information on each inmate's tattoos is only available for the most recent prison spell the inmate experience in Florida. Thus, the tattoo data provided are accurate for the most recent incarceration and release from prison, but may not represent the tattoos an inmate had during previous incarcerations. As a result, I am unable to examine changes in the effect of tattoos over time.[46] Due to the lack of information on how an inmate's tattoos change over time, I examine the effect of tattoos on prisoners released in or after 2008 assuming that five years is a reasonable time period where the amount tattoos may not change dramatically for most inmates. I consider inmates released from Florida prisons in 2008, 2009, and 2010, and track these inmates for returns to FDOC facilities within three years post release. Additionally, this three year follow-up period is consistent with several previous studies which examine recidivism as rearrest, reoffense, or reincarceration within three years following release.[47] After limiting the FDOC OBIS data to inmates released in 2008, 2009, or 2010, the final dataset used within my analysis consists of 97,156 inmates.

To measure days until recidivism, I utilize FDOC data on receipt and release dates of all inmates released between 2008 and 2010, into or out of FDOC prison facilities during three years post-release.[48] Recidivism length is calculated as the difference in days between an inmates' first release from prison between 2008 and 2010, and their next receipt into an FDOC prison facility, if any, during the follow-up period. As I limit the definition of recidivism to a three year follow-up period, inmates who were reincarcerated more than three years from their initial release are censored and listed as not returning to prison. The average number of days until recidivism for all inmates within the sample is 974 days. Table 3.1b presents summary statistics for tattooed inmates within my sample, separated by tattoo classification. When separated based on tattoo visibility, inmates with non-visible tattoos survived an average of 1003 days without reincarceration. Inmates with visible_2 tattoos, tattoos on the face, head, hands, neck, arms, or

[46] I am currently waiting on a response to a request to FDOC for access to tattoo data over time.
[47] For example, Benda and Toombs, 2002; Langan and Levin, 2002; Duwe and Donnay, 2008; Waters, 2012.
[48] The FDOC operates prisons within the state, whereas jails are under county supervision. Thus, I am unable to include time served at jails in this calculation because the FDOC OBIS database includes only prison receipts and releases.

legs, spent an average of 951 days in society without returning to prison, whereas inmates with tattoos specifically on their face, head, neck, or hands, returned to prison in 907 days on average.

Failure is a dummy variable indicating whether an inmate returned to incarceration during the three year follow-up period. Roughly 22% of inmates in my sample returned to prison during the three year follow-up period. [49]This calculated recidivism rate is comparable to those identified in FDOC publications, which place three-year recidivism rates for inmates released between 2004 and 2008 at an average of 31.5% (FDOC, 2013). When the sample is separated based on tattoo visibility, only 17% of non-visibly tattooed inmates returned to incarceration during the follow-up period. However, inmates with visible_2 tattoos has a recidivism rate of 27% during the follow-up period. Inmates with visible_1 tattoos, located on the head, face, neck, or hands, had the highest failure rate of 35% within the follow-up period, roughly double that of non-visibly tattooed inmates.

Next, I construct several variables to control for the effect of prior criminal history on recidivism. Inmates with prior criminal histories may be more likely to return to incarceration, as this may reflect a criminal lifestyle rather than an isolated incident.[50] Another area of previous research suggests that the prison environment may 'harden' offenders.[51] To control for the effect of prior criminal activity or incarcerations on future recidivism risk, I construct a variable that

---

[49] Although this recidivism rate may seem low compared to rates which include both jails and prisons, FDOC publications also consider only prisons operated by the State of Florida. The similarity between FDOC publications and my results suggests my calculations are accurate.

[50] Langan and Levin (2002) suggest that the number of prior offenses or incarcerations affect recidivism risk.

[51] Chen and Shapiro (2007) and Drago et al. (2011) find evidence that harsher prison conditions may increase recidivism. The FDOC OBIS database provides the custody classification of each inmates' most recent incarceration. For inmates who do not return to incarceration during the follow-up period, the custody level variable allows for the control of the effect of security level on recidivism. However, as FDOC only provides the custody description for the most recent incarceration, the custody variable for inmates who returned to incarceration during the follow-up period measures their second incarceration during the period. As such, the custody variable for inmates who recidivated does not provide a control for the effect of security level on recidivism.

counts the number of prior incarcerations of an inmate. This variable ranges from 1 to 16 prior incarcerations for inmates within my sample.

Additionally, it is possible that an inmate who was recently released from a long-term sentence may have greater difficulty adjusting to civilian life than an inmate sentenced to a shorter prison term. If that is the case, time served and recidivism should be positively related (Baumer, 1997). It is also possible that as the length of the prison sentence increases, the likelihood of recidivism decreases. To control for the potential effect of prison term length on recidivism, I construct a variable which measures the length in days of the most recent sentence each inmate was released from during the follow-up period.[52]. The length of the most recent incarceration for inmates within my sample ranges from 365 days (1 year) to 367,745 days (1,000 years).[53]

I also control for violent and property offenses within each inmates' history. The FBI classifies violent crimes as inclusive of rape, robbery, aggravated assault, and murder.[54] Research suggests that violent offenders are more likely to recidivate than similar non-violent offenders (Baumer, 1997; Langan and Levin, 2002). Offenders with property crimes may also be more likely to recidivate as property crimes may be a source of income for these individuals once released (Baumer, 1997; Langan and Levin, 2002).

The FDOC data provides a description of each offense in an inmates' criminal history. To create dummy variables to control for prior violent and property offenses, I search within the text description provided[55]. The dummy variable controlling for violent crimes in an inmate's history

[52] Findings on whether prison term lengths affect recidivism are mixed. See Baumer (1997) for additional explanations.
[53] I consider only prison sentences, which in Florida start at a minimum of 365 days. Shorter sentences are served in jails. Inmates serving multiple life sentences have prison sentences that compile to 1,000 years.
[54] Descriptions of property and violent crime descriptions are taken from www.FBI.gov.
[55] I create dummy variables for each of the FBI classifications by searching the FDOC offense descriptions for these words or their abbreviations. For example, the FDOC descriptions abbreviate murder to "mur".

is constructed as equal to one if an inmate had a previous rape, robbery, homicide, or murder in their FDOC record, and equal to zero if not.[56] The same process is used to create a dummy variable to control for the FBI's list of property crimes; burglary, larceny, motor vehicle theft. Within my sample, roughly 22% of inmates had prior violent offenses, and roughly 35% had prior property crime offenses at the time of release.

To control for demographic factors related to recidivism, I construct control variables for age, race, and gender of inmates at the time of release. Previous research suggests that age, gender, race, and previous criminal activity are the most consistent predictors of recidivism.[57]. Research on the relationship between gender and recidivism suggests recidivism risk is higher for men than women[58]. Within my analysis, male inmates account for roughly 88% percent of the sample.

Race is also an important determinant for recidivism and previous studies suggest Black inmates are more likely to recidivate than White inmates[59]. Race is defined within my analysis using the classifications from the FDOC OBIS database (Black, White, Hispanic, Asian or Pacific Islander, American Indian, or unknown). Roughly 50% of inmates within my sample are

---

[56] The construction of this variable is limited in that the FDOC offense list may abbreviate or describe offenses differently than the FBI. For example, a search for "rape" returns no results, but there are many sexual assault offenses listed within this description. This limitation may underestimate the number of criminals with previous violent crime offenses.

[57] These variables are consistently found to be main determinants of recidivism in the following studies: Jurik, 1983; Visher and Linster, 1990; Hanley and Latessa, 1997; Gainey et al., 2000; Kruttschnitt et al., 2000; Benda and Toombs, 2002; Spohn and Holleran, 2002. Previous research suggests less consistently that employment status, marital status, and drug use post-release affect recidivism risk, with marriage and employment negatively affecting recidivism and drug use positively affecting recidivism. Requests for data on those variables from FDOC was denied due to confidentiality issues. Kling (2006) matches encrypted social security numbers from FDOC to those listed on unemployment claims from Florida's unemployment insurance office, providing a link between inmates and employment status post-release. However, this data is not publically available and requests to access it were denied.

[58] See Baumer, 1997; Gainey et al., 2000; Langan and Levin, 2002; Spohn and Holleran, 2002; Duwe and Donnay, 2008; Waters 2012.

[59] The following studies find black inmates are more likely to recidivate than white inmates: Blumstein et al., 1986; Beck and Shipley, 1987; Anderson et al., 1991; Helpburn and Albonetti, 1994; Gendreau et al., 1996; Beck and Shipley 1997; Benda and Toombs, 2002; Langan and Levin, 2002; Spohn and Holleran, 2002; Langan et al., 2003; Kubrin and Stewart, 2006; Bales and Mears, 2008; Kohl et al., 2008

White, 46% are Black, 3.6% are Hispanic, and the remaining 0.4% are either Asian, Pacific Islander, American Indian, or Unknown.

Age at release has also been identified within previous research to negatively affect recidivism risk[60]. It is possible that this is a result of learning by doing, and that criminals become more efficient over time. Another possibility is that once older criminals find employment they substitute into more stable lifestyles (Uggen, 2000). Fifteen years of age is the minimum age at release within the sample and the maximum age is 88.[61] [62] I limit the sample to exclude inmates who are listed in the FDOC database but are deceased as they do not have the opportunity to commit future crimes.

3.3 Methodology

When estimating recidivism, it is important to take into account both the timing and occurrence of an individual's return to prison. Binary indicators which account only for the occurrence of recidivism, treat ex-offenders that return to prison early in the follow-up period identical to those that return to prison several months or years later. Ignoring these potential differences in the length of time spent outside of prison is problematic because the additional time an ex-offender survives in society translates into time the department of corrections is not responsible for the cost of housing that individual.

[60] Many studies find that criminal activity dissipates as age increases. For example, please see Visher et al., 1991; Hepburn and Albonetti, 1994; Baumer, 1997; Benedict et al., 1998; Uggen, 2000; Benda and Toombs, 2002; Spohn and Holleran, 2002; Windzio, 2006; Duwe and Donnay, 2008, Lozano et al., 2010, Waters, 2012.

[61] The FDOC OBIS database contains a birthdate for each inmate, which I use to calculate age at release for each inmate's first release during the follow-up period.

[62] Cross-checks of my calculation of age at release with the FDOC OBIS database for the inmates' whose ages are the minimum and maximum verify the validity of the calculation.

The number of days between an inmate's release from prison and reincarceration is defined as the survival length for each inmate and a failure dummy variable indicates whether or not an inmate returned to incarceration during the follow-up period. x_i is defined as the vector of independent variables related to the likelihood of recidivism for individual i. Then, I define γ as a vector of coefficients of x_i. The initial survivor function for inmate i is

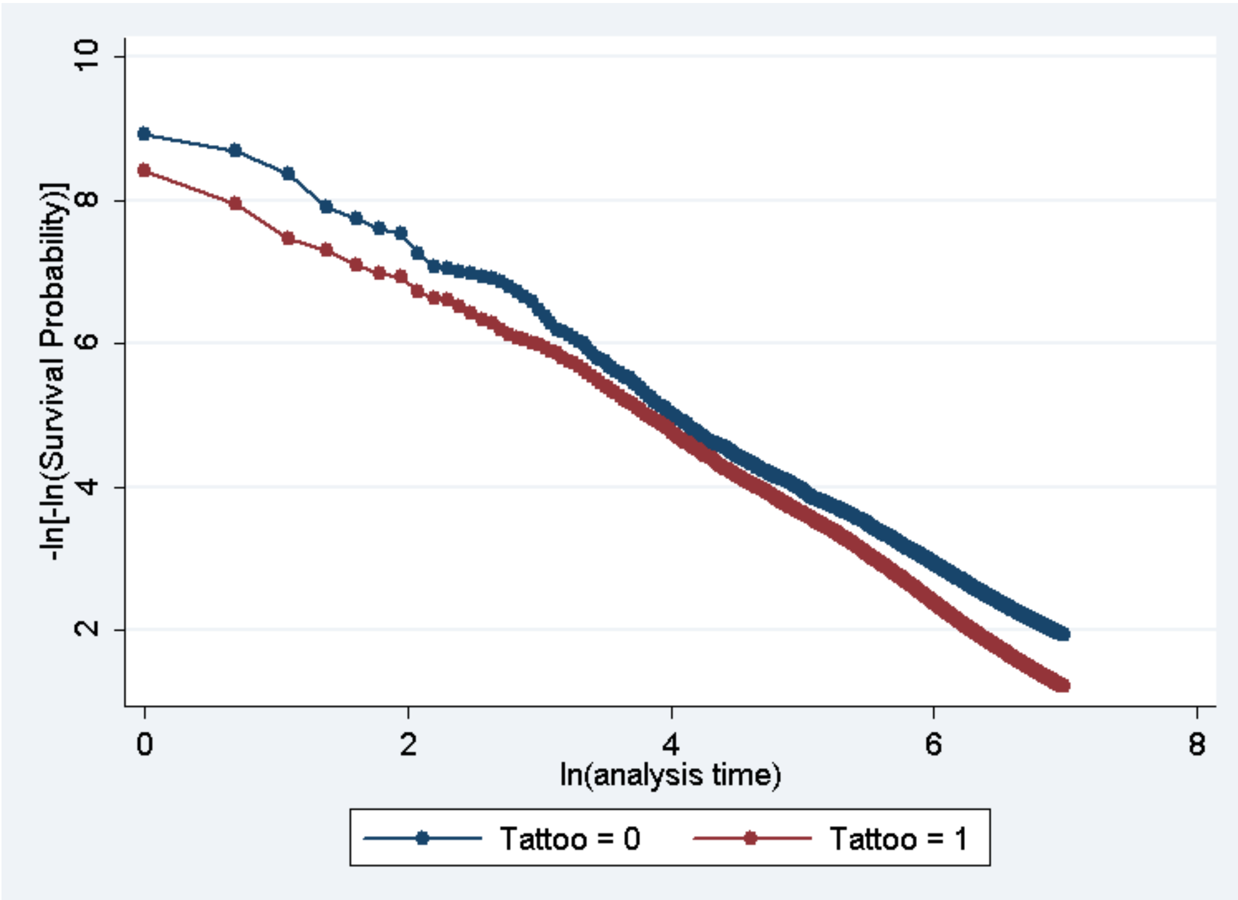
$$(1)\ S_i = \exp\left[-\int_0^t h(T; x_i\gamma)dT\right]$$

Where S_i indicates survival time of inmate i in society before returning to prison, $h(.)$ indicates the hazard rate of returning to prison, t indicates the current time period, and T indicates the total number of time periods considered within the analysis.

Several previous articles utilize the Cox proportional hazards model to study recidivism (Baumer, 1997; Benda and Toombs, 2002; Windzio, 2006, Duwe and Donnay, 2008). This model assumes proportionality of the hazard ratios across treatment and non-treatment groups. To check whether the proportionality assumption holds for my data, I examine log-log survival plots for tattooed inmates versus non-tattooed inmates, as shown in Figure 3.3. Parallel survival plots would indicate the proportional hazards assumption is not violated. However, as seen in figure 3.3, the log-log survival functions for tattooed and non-tattooed inmates within my sample are not parallel. A further test of the proportionality assumption using Schoenfeld residuals reveals that the assumption is violated within my data and thus a proportional hazards model is inappropriate within this analysis.[63] The functional form of $h(.)$ Must be flexible enough to fit hazard rates found within the dataset (Douglas, 1998). Using the Cox proportional hazards model places an overly restrictive functional form assumption on the data within my analysis.

[63] Although figure 3.3 only depicts the violation of the proportionality assumption for the tattoo dummy variable, both visibility variables, visible_1 and visible-2, also violate this assumption.

Figure 3.3: Log-log Plots of Survival Functions for Tattooed versus Non-tattooed Inmates using Cox Proportional Hazard Estimation.



Given that using a proportional hazard model to examine the data used within my analysis would be inappropriate, I use an accelerated failure time (AFT) survival model with a log-logistic distribution to estimate the relationship between visible tattoos and days until recidivism.[64] The log-logistic distribution for the starting hazard is a flexible functional form which allows for a non-monotonic hazard function. The starting hazard function for the log-logistic survival model is given by the following equation:

---

[64] The log-logistic distribution provides the best fit to my data however the use of other distributions within the AFT framework produces similar results to those found within this paper.

(2) $h(t; x_i\gamma) = \frac{[\exp(x_i\gamma)\lambda t^{\lambda-1}]}{[1+\exp(x_i\gamma)t^{\lambda}]}$

Where λ is a shape parameter describing the relationship between hazard and duration. For log-logisitc models, $\lambda < 1$ indicates hazard declines with duration and $\lambda > 1$ indicates hazard rises and then falls.

I begin by estimating the days until recidivism for the entire sample of ex-offenders released during 2008, 2009, and 2010. However, if selection into getting a tattoo indicates some type of unobservable characteristic that makes an inmate more likely to commit future crimes and thus return to incarceration, it is not surprising that the results show that non-tattooed inmates survive longer. As a first step to addressing this selection effect, I also examine only the subset of tattooed inmates in my analysis.

However, the same selection effect can be identified with regards to tattoo location decisions. An ex-offender who chose to get a visible tattoo may be inherently different in observable characteristics than an ex-offender who chose to locate their tattoo somewhere hidden by clothing. To attempt to mitigate some of these selection effects, I again restrict my sample and consider only inmates with visible tattoos.

Concerns about the effect of unobservable characteristics on recidivism still remain. However, given the available data, these are the most reasonable estimates I can currently obtain. Additionally, the use of survival methodology to address the timing and occurrence of recidivism is still an improvement over the current literature.

Although the use of a survival model is advantageous over probit or logit regressions as it takes into account both the timing and occurrence of recidivism, standard survival models inherently assume that all observations eventually experience failure, although some may be censored in the data. In the case of recidivism, this assumption implies that all ex-offenders will eventually return to prison and in the cases where this does not occur within the data, it is because the time frame ends before the failure can occur.

Split-population duration models do not require eventual failure for all observations, and instead allow for the possibility that some observations never experience failure. Duration models of this type are directly applicable to recidivism given that some ex-offenders will never return to prison. In a future draft of this paper, I will detail the split-population duration model and present results under that specification.

3.4 Results

a. Survival Results for Entire Sample

Table 3.2a contains estimates for the log-logistic survival time of ex-offenders using the entire sample of inmates released during 2008, 2009, or 2010. The baseline specification is presented in column (1), column (2) expands upon column (1) with the inclusion of control variables mentioned earlier, and column (3) expands upon column (2) by including county fixed effects to control for county-level differences that may affect recidivism rates, such as differences in clearance rates across counties.

i. *Estimated Survival Length Results*

Using the constant from the log-logistic survival estimates, an estimate for the median predicted baseline survival length can be obtained. Recall that within this analysis, recidivism is measured as reincarceration, and thus survival length is the number of days an ex-offender lives in society without returning to incarceration.

Table 3.2a: Loglogistic Survival Regressions of Tattooed versus Non-Tattooed Inmates.			
	(1)	(2)	(3)
Tattoo	-0.637***	-0.395***	-0.391***
	(0.016)	(0.017)	(0.017)
Black		-0.026	-0.029
		(0.165)	(0.166)
Asian/Pacific Islander		-0.014	-0.087
		(0.787)	(0.778)
Hispanic		0.011	-0.002
		(0.168)	(0.169)
White		-0.184	-0.164
		(0.165)	(0.166)
American Indian		-0.316	-0.164
		(0.294)	(0.289)
Age at release		0.051***	0.050***
		(0.001)	(0.001)
Gender		-0.263***	-0.266***
		(0.022)	(0.022)
Violent offense in history		0.061***	0.040***
		(0.015)	(0.015)
Property offense in history		-0.043***	-0.064***
		(0.013)	(0.013)
Length of last incarceration		-0.000***	-0.000***
		(0.000)	(0.000)
Number of previous incarcerations		-0.426***	-0.428***
		(0.005)	(0.005)
Constant	8.506***	7.910***	7.658***
	0.017	0.169	0.175
County Fixed Effects	No	No	Yes
Observations	97,040	95,645	95,645

Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating p<0.01, p<0.05, and p<0.1 respectively. The dependent variable in this analysis is comprised of two parts, a dummy variable indicating whether or not an inmate returned to incarceration during the three year follow-up period, and a timing variable indicating the number of days an inmate 'survived' in society. The tattoo variable is a dummy variable indicating whether or not an inmate is tattooed. Demographic control variables include gender, race (Black, White, Hispanic, Asian or Pacific Islander, American Indian), and Age at release. Length of the most recent prison term, violent or property crimes in an inmate's history, and the number of previous incarcerations are also controlled for. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed.

The median predicted baseline survival length from the baseline specification is 4,944 days.[65] Based on the estimates presented in the baseline specification, having a tattoo decreases the median expected survival length by 2,329 days. Upon the inclusion of control variables in column (2), the median predicted baseline survival length drops to 2,724 days. Once controls are included, ex-offenders with tattoos survive on average 1,697 days less than ex-offenders without tattoos. Finally column (3) presents the most complete specification within table 3.2a, and includes estimates from log-logistic survival regressions of the tattoo dummy variable, all control variables, and county-level fixed effects. The median predicated baseline survival length based on the estimates presented in column (3) is 2,118 days. Based on these estimates, ex-offenders without tattoos survive on average 1,249 days longer than ex-offenders with tattoos.

The results for control variables for gender, previous property offenses, and the number of previous incarcerations are consistent with previous literature. The gender dummy variable indicates that female offenders survive longer than male offenders. Ex-offenders with property offenses in their criminal histories tend to return to incarceration faster than those without property offenses.[66] As the number of previous incarcerations increases, the estimated survival time decreases, which is consistent with the finding that inmates who are incarcerated often are more committed to or involved in a criminal lifestyle (Baumer, 1997).

There are some findings for the control variables within my analysis which diverge from previous work. Race does not significantly impact survival of ex-offenders within my analysis.[67]

---

[65] Although the follow-up period within my analysis is limited to a three year period, or 1095 days, it is not surprising that the baseline survival length exceeds that threshold given that roughly 78% of ex-offenders in my sample do not return to incarceration within three years, and that in the baseline specification I have not controlled for some factors which serve to decrease expected survival time.

[66] Baumer, 1997 and Langan and Levin, 2002 also find this result.

[67] Although other papers find that race has a differential effect on recidivism (Blumstein et al., 1986; Beck and Shipley, 1987; Anderson et al., 1991; Helpburn and Albonetti, 1994; Gendreau et al., 1996; Beck and Shipley 1997; Benda and Toombs, 2002; Langan and Levin, 2002; Spohn and Holleran, 2002; Langan et al., 2003; Kubrin and Stewart, 2006; Bales and Mears, 2008; Kohl et al., 2008)) this may be a feature of small sample sizes used in some

Additionally, although the length of last incarceration is significantly related to survival time, the estimated impact equals zero, and thus the effect of the length of the last incarceration is not economically significant. Finally, based on my estimates ex-offenders convicted of previous violent offenses are expected to survive longer than those without previous violent offense convictions. Using column (3) from Table 3.2a, the coefficient on violent offense in history of 0.040 indicates an increase in median predicted baseline survival time of 220 days. However, in later specifications I limit the sample to only tattooed inmates and the significance of this result disappears. Overall, the estimates from columns (1), (2), and (3) all indicate that having a tattoo has a negative and significant relationship with survival length.[68]

ii. ***Time Ratio Results***

Table 3.2b presents the same specifications as table 3.2a, instead listing time ratio results, which offer a different interpretation than log-logistic coefficients. Time ratio coefficients represent the relationship between a one unit change in a given variable and estimated survival length.

---

analyses. It is also possible that the lack of significance of race in affecting recidivism is a unique feature of the Florida-specific data I am using

[68] I have also run regressions looking only at the subsets of male versus female offenders, black versus white offenders, violent versus non-violent offenders, and offenders with and without property crimes in their history. The results consistently show a negative and significant relationship between the likelihood of survival and the instance of a visible tattoo. To see the results of these robustness checks, please contact the author.

Table 3.2b: Loglogistic Survival Regressions of Tattooed versus Non-Tattooed Inmates. **Time Ratios Reported.**

	(1)	(2)	(3)
Tattoo	0.529***	0.674***	0.676***
	(0.008)	(0.011)	(0.011)
Black		0.974	0.972
		(0.161)	(0.161)
Asian/Pacific Islander		0.986	0.916
		(0.776)	(0.713)
Hispanic		1.012	0.998
		(0.170)	(0.169)
White		0.832	0.849
		(0.137)	(0.141)
American Indian		0.729	0.713
		(0.214)	(0.207)
Age at release		1.052***	1.052***
		(0.001)	(0.0009)
Gender		0.769***	0.767***
		(0.017)	(0.017)
Violent offense in history		1.063***	1.041***
		(0.016)	(0.015)
Property offense in history		0.958***	0.938***
		(0.013)	(0.012)
Length of last incarceration		1.000***	1.000***
		(0.000)	(0.000)
Number of previous incarcerations		0.653***	0.652***
		(0.003)	(0.003)
Constant	4945.164***	2724.980***	2116.502***
	(83.318)	(460.669)	(369.828)
County Fixed Effects	No	No	Yes
Observations	97,040	95,645	95,645

Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating p<0.01, p<0.05, and p<0.1 respectively. The dependent variable in this analysis is comprised of two parts, a dummy variable indicating whether or not an inmate returned to incarceration during the three year follow-up period, and a timing variable indicating the number of days an inmate 'survived' in society. The tattoo variable is a dummy variable indicating whether or not an inmate is tattooed. Demographic control variables include gender, race (Black, White, Hispanic, Asian or Pacific Islander, American Indian), and Age at release. Length of the most recent prison term, violent or property crimes in an inmate's history, and the number of previous incarcerations are also controlled for. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed.

Time ratio values greater than one signify that unit increases in the given variable correspond to increase in the survival length by the time ratio subtracted by 1. Examining table 3.2b column (3) shows a statistically significant time ratio of 1.052 for the variable, age at release. This indicates that a one year increase in age at release is related to an increase in the expected survival time of 5.2%. This result is consistent with previous research suggesting that as inmates age they are less likely to recidivate (Uggen, 2000).

Time ratios less than one correspond to percent decreases in predicted survival time for each unit increase in the variable being considered. Again looking at table 3.2b column (3), the time ratio for the gender variable is 0.767, which corresponds to a decrease in predicted survival time by 23.3%. This indicates that survival times for male inmates are on average 23.3% lower than predicted survival times for female inmates.

The baseline specification in table 3.2b suggests that inmates with tattoos have an expected survival time 47.1% lower than inmates without tattoos. When control variables are included in column (2), inmates with tattoos have an estimated survival time 32.6% lower than inmates without tattoos. Column (3) includes control variables and county fixed effects to control for differences in clearance rates across counties. The results from column (3) indicate that inmates with tattoos have an expected survival time 32.4% lower than inmates without tattoos.

The results presented in tables 3.2a and 3.2b are limited given that inmates with tattoos may be inherently different in unobservable characteristics than non-tattooed inmates due to self-selecting into getting a tattoo. In order to attempt to remove the self-selection effect of getting a tattoo from the comparison of inmates, I now consider two subsets of inmates who self-selected into being tattooed.

b. *Survival Results for Tattooed and Visibly Tattooed Subsamples*

The results from the regressions on tattooed and visibly tattooed inmate subsamples are presented in tables 3.3a and 3.3b. Columns (1) and (2) in tables 3.3a and 3.3b consider the tattooed subsample of inmates. Column (3) in tables 3.3a and 3.3b is further limited to include only the subsample of inmates who self-selected into receiving visible tattoos. Again, table 3.3a presents the log-logistic regression coefficients and table 3.3b presents the time ratio coefficients. Estimates for control variables in all columns within tables 3.3a and 3.3b follow the expected signs mentioned earlier.

i. *Estimated Survival Length Results*

The results from column (1) table 3.3a suggest that ex-offenders with tattoos on the face, head, neck, or hands return to incarceration faster than other tattooed ex-offenders. Specifically, visible_1 tattooed ex-offenders recidivate 714 days earlier than other tattooed ex-offenders. The results from column (2) compare ex-offenders with tattoos on face, head, neck, hands, arms, or legs, to ex-offenders with tattoos in other locations. The results from the specification in column (2) suggest that ex-offenders with visible_2 tattoos have a predicted median survival length 530 days shorter than ex-offenders with non-visible tattoos.

Table 3.3a: Loglogistic Survival Regressions of Inmate Subsamples.			
	(1)	(2)	(3)
	Visible_1	Visible_2	Visible_3
Visibility classification	-0.320***	-0.203***	-0.306***
	(0.013)	(0.028)	(0.013)
Black	-0.009	0.030	-0.028
	(0.173)	(0.171)	(0.174)
Asian/Pacific Islander	-0.190	-0.182	-0.340
	(0.746)	(0.768)	(0.780)
Hispanic	-0.023	-0.012	-0.045
	(0.177)	(0.174)	(0.178)
White	-0.160	-0.133	-0.187
	(0.173)	(0.171)	(0.174)
American Indian	-0.168	-0.179	-0.217
	(0.328)	(0.326)	(0.333)
Age at release	0.053***	0.058***	0.054***
	(0.001)	(0.001)	(0.001)
Gender	-0.287***	-0.250***	-0.317***
	(0.024)	(0.024)	(0.026)
Violent offense in history	0.025	0.029*	0.026
	(0.016)	(0.016)	(0.016)
Property offense in history	-0.055***	-0.058***	-0.051***
	(0.014)	(0.014)	(0.014)
Length of last incarceration	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Number of previous incarcerations	-0.450***	-0.458***	-0.449***
	(0.006)	(0.006)	(0.006)
Constant	7.374***	7.263***	7.370***
	(0.183)	(0.183)	(0.185)
County Fixed Effects	Yes	Yes	Yes
Observations	66,574	66,574	60,843

Columns (1) and (2), present results for the tattooed subsample, column (3) presents results for the visibly tattooed subsample of inmates. Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating $p<0.01$, $p<0.05$, and $p<0.1$ respectively. The dependent variable in this analysis is comprised of two parts, a dummy variable indicating whether or not an inmate returned to incarceration during the three year follow-up period, and a timing variable indicating the number of days an inmate 'survived' in society. These regressions are limited to the tattooed subsample. The visible_1 variable is a dummy variable indicating whether or not an inmate has a tattoo located on the face, head, neck or hands. Visible_2 is a dummy variable indicating whether or not an inmate has a tattoo located on the face, head, neck, hands, arms, or legs. The visible_3 classification compares the effect of having a visible_1 tattoo (face, head, neck, or hands) within the visibly tattooed subsample. That is, column 3 is limited to only inmates with either visible_1 or visible_2 tattoos. Demographic control variables include gender, race (Black, White, Hispanic, Asian or Pacific Islander, American Indian), and Age at release. Length of the most recent prison term, violent or property crimes in an inmate's history, and the number of previous incarcerations are also controlled for. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed.

However, the same caveat from earlier regarding self-selection still applies. It is possible that individuals choosing visible tattoo locations are inherently different from those choosing to get tattoos in non-visible locations. These differences may be unobservable and correlated with factors affecting recidivism. In an attempt to minimize this self-selection even further, column (3) considers the effect of a tattoo located on the face, head, neck, or hands, a visible_1 tattoo, on days until recidivism within the subset of visibly tattooed inmates. Recall, tattoos are considered visible if located on head, face, neck, hands, arms, or legs. Column (3) considers only those inmates who self-selected into receiving visible tattoos, in turn minimizing the unobservable differences associated with choosing to receive a visible tattoo. The variable of interest in column (3) is visible_1, which represents tattoos located on the head, face, neck, or hands of an individual.

The results from column (3) follow a similar pattern. As before, inmates with tattoos located on their face, head, neck, or hands, return to incarceration faster than inmates with tattoos in other visible locations. Ex-offenders with visible_1 tattoos located on their face, head, neck, or hands fail 674 days earlier than ex-offenders with visible tattoos in other locations.

ii. ***Time Ratio Results***

The time ratio results for these regressions are presented in table 3.3b. Column (1) suggests that inmates with visible_1 tattoos have an expected survival time 27.4% lower than ex-offenders with tattoos that are not located on the face, head, neck, or hands. Column (2) presents a similar estimate suggesting that ex-offenders with visible_2 tattoos have an expected survival time 18.4% lower than ex-offenders with non-visible tattoos. Column (3), which contains estimates examining only ex-offenders with visible tattoos, suggests that inmates with tattoos on their head, face, neck, or hands return to incarceration 26.4% faster than ex-offenders with visible tattoos not located on the head, face, neck, or hands.

Table 3.3b: Loglogistic Survival Regressions of Inmate Subsamples. **Time Ratios Reported.**			
	(1)	(2)	(3)
Visibility classification	0.726***	0.816***	0.736***
	(0.010)	(0.023)	(0.010)
Black	0.991	1.031	0.972
	(0.172)	(0.176)	(0.170)
Asian/Pacific Islander	0.827	0.834	0.712
	(0.617)	(0.640)	(0.555)
Hispanic	0.977	0.988	0.956
	(0.173)	(0.172)	(0.170)
White	0.852	0.875	0.830
	(0.148)	(0.149)	(0.145)
American Indian	0.846	0.836	0.805
	(0.277)	(0.273)	(0.268)
Age at release	1.054***	1.059***	1.055***
	(0.001)	(0.001)	(0.001)
Gender	0.750***	0.779***	0.728***
	(0.018)	(0.019)	(0.019)
Violent offense in history	1.026	1.029*	1.026
	(0.016)	(0.016)	(0.017)
Property offense in history	0.946***	0.943***	0.950***
	(0.013)	(0.013)	(0.013)
Length of last incarceration	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)
Number of previous incarcerations	0.638***	0.632***	0.639***
	(0.004)	(0.000)	(0.004)
Constant	1594.642***	1426.883***	1588.013***
	(292.423)	(260.370)	(293.848)
County Fixed Effects	Yes	Yes	Yes
Observations	66,574	66,574	60,843

Columns (1) and (2), present results for the tattooed subsample, column (3) presents results for the visibly tattooed subsample of inmates. Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating p<0.01, p<0.05, and p<0.1 respectively. The dependent variable in this analysis is comprised of two parts, a dummy variable indicating whether or not an inmate returned to incarceration during the three year follow-up period, and a timing variable indicating the number of days an inmate 'survived' in society. These regressions are limited to the tattooed subsample. The visible_1 variable is a dummy variable indicating whether or not an inmate has a tattoo located on the face, head, neck or hands. Visible_2 is a dummy variable indicating whether or not an inmate has a tattoo located on the face, head, neck, hands, arms, or legs. The visible_3 classification compares the effect of having a visible_1 tattoo (face, head, neck, or hands) within the visibly tattooed subsample. That is, column 3 is limited to only inmates with either visible_1 or visible_2 tattoos. Demographic control variables include gender, race (Black, White, Hispanic, Asian or Pacific Islander, American Indian), and Age at release. Length of the most recent prison term, violent or property crimes in an inmate's history, and the number of previous incarcerations are also controlled for. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed.

3.5 Conclusions

This paper explores the relationship between visible tattoos and recidivism. Within this analysis I measure recidivism as re-incarceration within a FDOC facility within a three year follow-up period. This paper makes two contributions to the literature. First, I develop two classifications of tattoo visibility based on different types of workplace attire. Second, this paper expands on an existing literature on criminal signaling mechanisms and examines whether ex-offenders with visible tattoos return to incarceration faster than ex-offenders with non-visible tattoos. This finding is robust to the different types of visibility developed within the paper.

This study has a few key limitations. First, the estimates presented in this paper represent relationships and are not causal effects. Although I attempt to eliminate some of the selection effects associated with choosing to get a tattoo, I cannot control for unobservable factors related to the choice to get a tattoo. Additionally, individuals who choose to get highly visible tattoos (visible_1) may be inherently different from individuals who choose to get tattoos that can be covered in some cases (visible_2). Given my current dataset, I am unable to obtain causal estimates. Second, the data only contain information on reincarceration in prisons in Florida. Thus, I have no information on rearrest, time spent in jail, or crimes committed outside Florida. Given this limitation I cannot consider definitions of recidivism tied to jail time or rearrest. Thus, it is possible I am underestimating the amount of recidivism occurring. Future research should examine causal effects and the additional recidivism tied to jail and out-of-state crimes.

The FDOC website lists the daily average cost of housing an inmate at $47.50 and the average annual cost per inmate at $17,338. Looking at the most complete specification, in table 3.3b column (3), the decrease in expected survival length of 419 days, equates to a cost of $19,903 per inmate with a visible_1 tattoo. Within the FDOC sample of inmates released during

2008, 2009, or 2010, 20,990 inmates have tattoos located on their head, face, neck, or hands. The per inmate cost of $19,903 adds up to a total cost of almost $418 million in housing costs over the three release years I consider. Of course, this back of the envelope calculation may be imprecise; however it reflects an important finding regarding the impact of tattoos as a signaling mechanism for ex-offenders to employers. Future research in this area should be expanded to consider the causal effect of personal appearance on inmate survival post-release.

Chapter 4
Does Distance between Residence and Incarceration Facility Affect Recidivism? Evidence from the Florida Department of Corrections

4.1 Introduction

Previous research suggests familial support is an important factor for reducing the risk of recidivism and that visitation while incarcerated reduces the risk of reoffense upon release (Bales and Mears, 2008). However in 2004, 62 percent of state inmates and 84 percent of federal inmates served time over 100 miles from their residence at the time of arrest (The Sentencing Project, 2009). As distance between residence and prison increases, so too does the cost of visitation for family members of incarcerated individuals. That relationship implies that as distance increases visitation frequency declines. If inmates receiving visits while incarcerated are less likely to return to prison in the future, it is possible that housing inmates long distances from potential visitors may positively affect future crime rates.

However some research concludes that the expectation of serving time in an isolated area may serve as a deterrent for criminal behavior, arguing that siting prisons in isolated locations deters crime by increasing the costliness of incarceration (Bedard and Helland, 2004). Increasing the isolation of female penitentiaries may reduce both violent and property crime rates in the area (Bedard and Helland, 2004). Drago et al. (2011) also examine the relationship between distance and recidivism risk and find evidence of a positive relationship. This suggests as distance to the main town increases, the probability of rearrest during the follow up period increases. They argue that this may be due to the lack of volunteers and religious figures visiting more isolated prisons.

Taken together, these two studies reach conflicting conclusions. For women, the expectation of serving time far from home is found to deter female crime (Bedard and Helland, 2004). However, when looking at Italian inmates Drago et al. (2011) find that inmates who serve time in geographically isolated prisons are more likely to reoffend upon release. Despite these conflicting findings, few studies have focused specifically on the relationship between home to prison distance and recidivism.

Distance between prison and the home of family and friends is an important determinant of whether or not visitations occur. As distance increases so too do transportation costs for potential visitors. This paper contributes to the literature by focusing on the relationship between home to prison distance and recidivism. If distance is related to recidivism risk, either positively or negatively, then correctional policy may prioritize geographic placement of inmates to reduce crime and correctional costs in the future.

Both Bedard and Helland (2004) and Drago et al. (2011) measure a prison's geographic isolation relative to the city. However, if an inmate's friends and family do not live close to the city, then distance between prison and city is not the relevant measure. I assume that the residence to which an inmate is released is highly correlated with the location of potential visitors. Using inmate-level data from the Florida Department of Corrections (FDOC), I examine whether inmates incarcerated farther from their residence return to incarceration faster or more frequently than inmates housed closer to home. The unique data from FDOC provide the address to which an inmate is released and the incarceration facility for prison spells of inmates in Florida. The release address provides a unique insight into where an inmate's support system likely resides. Thus, my measure of distance is based on the distance between the inmate's planned residence upon release and the incarceration facility.

To test the hypothesis that home to prison distance is related to recidivism, I begin with Ordinary Least Squares regressions and examine the average relationship between distance and recidivism. Next, I use a survival methodology to account for both the timing and occurrence of recidivism. This individual-level dataset allows for the control of age, gender, race, incarceration history, differences across counties, and whether previous crimes were violent or property related. I examine the sample of Florida offenders who were not currently incarcerated as of October 2013, and follow those offenders within Florida until January 2015.

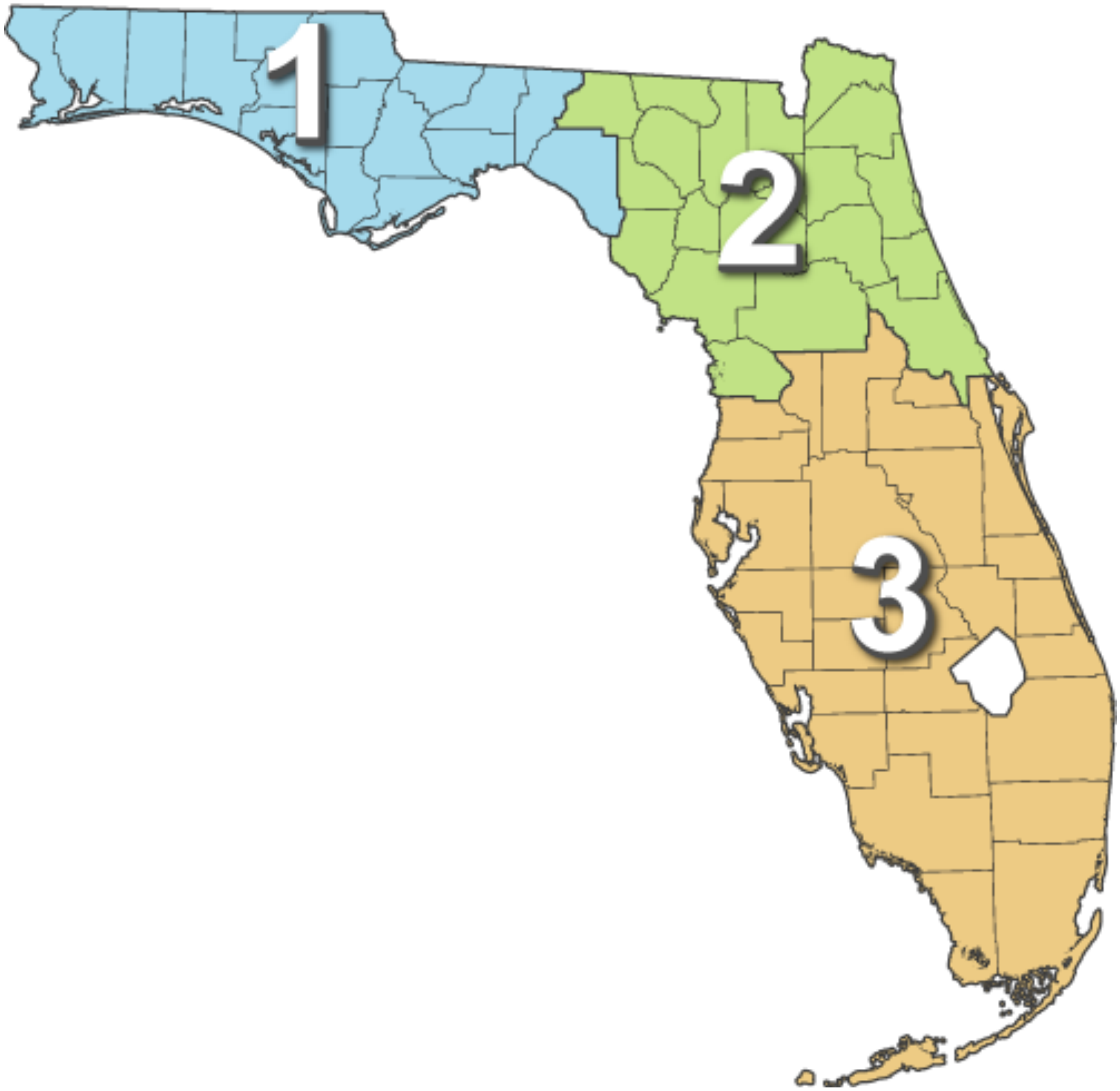
Although FDOC officials attempt to place inmates in facilities close to their homes, the majority of inmates, roughly 75%, come from South or Central Florida, and the majority of prison beds are located in North Florida. This translates into a spatial mismatch of inmates to beds. As such, all inmates cannot be placed close to home. The FDOC inmate classification bureau assigns inmates to their initial placement within an FDOC facility. According to the bureau, these initial placements are based primarily on bed space and as such most inmates are not initially placed close to home.

4.2 Layout of Correctional Facilities in Florida[69]

The Florida Department of Corrections (FDOC) separates its facilities into three regions across the state. Region 1 is comprised of North Florida, Region 2 is Central Florida, and Region 3 is South Florida. A depiction of how these regions are separated across the state is shown in Figure 4.1.

[69] Unless otherwise stated, the information in this section comes from http://www.dc.state.fl.us/facilities.

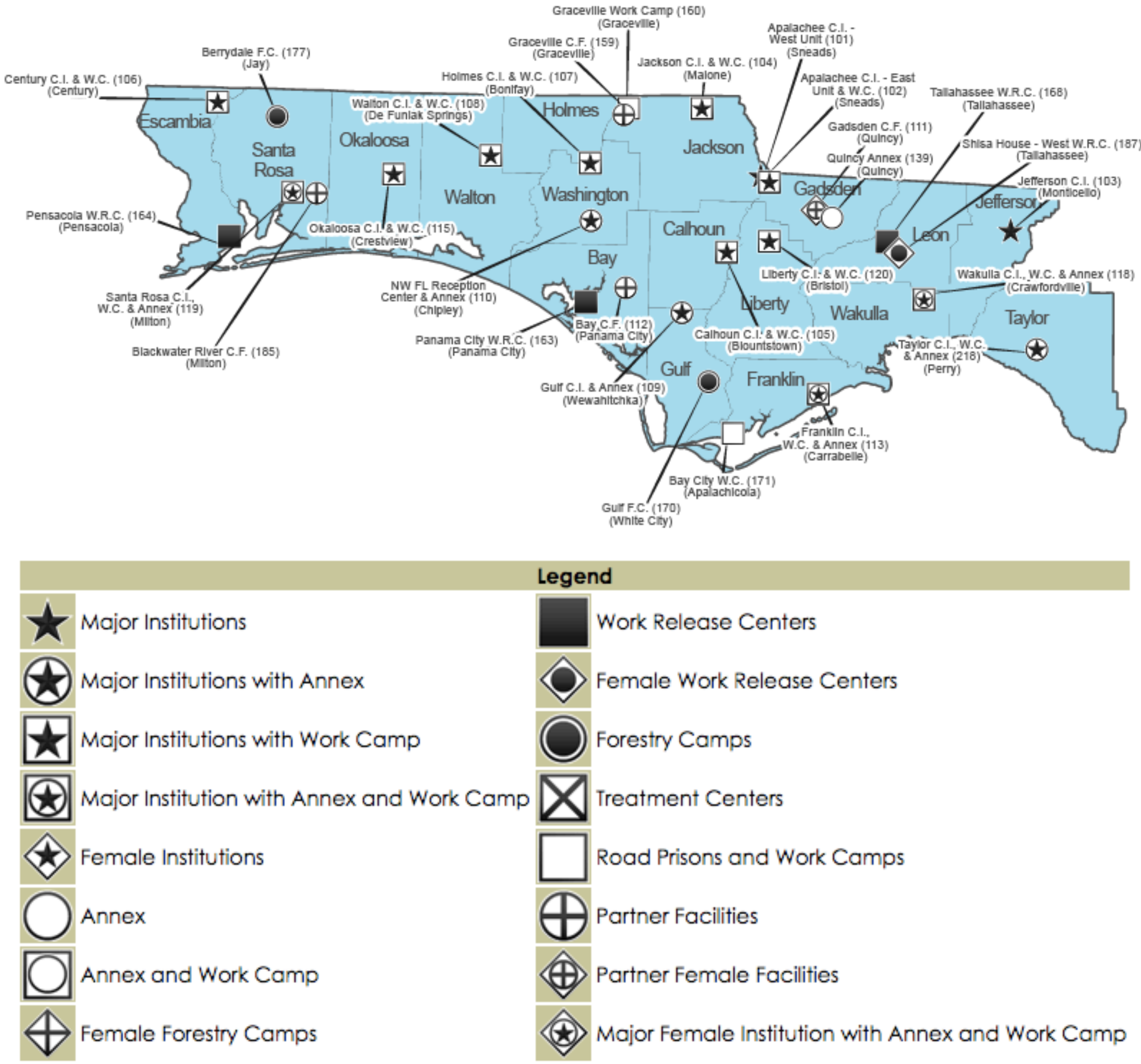
Figure 4.1: Map of FDOC Regions.



Source: FDOC, October 2014

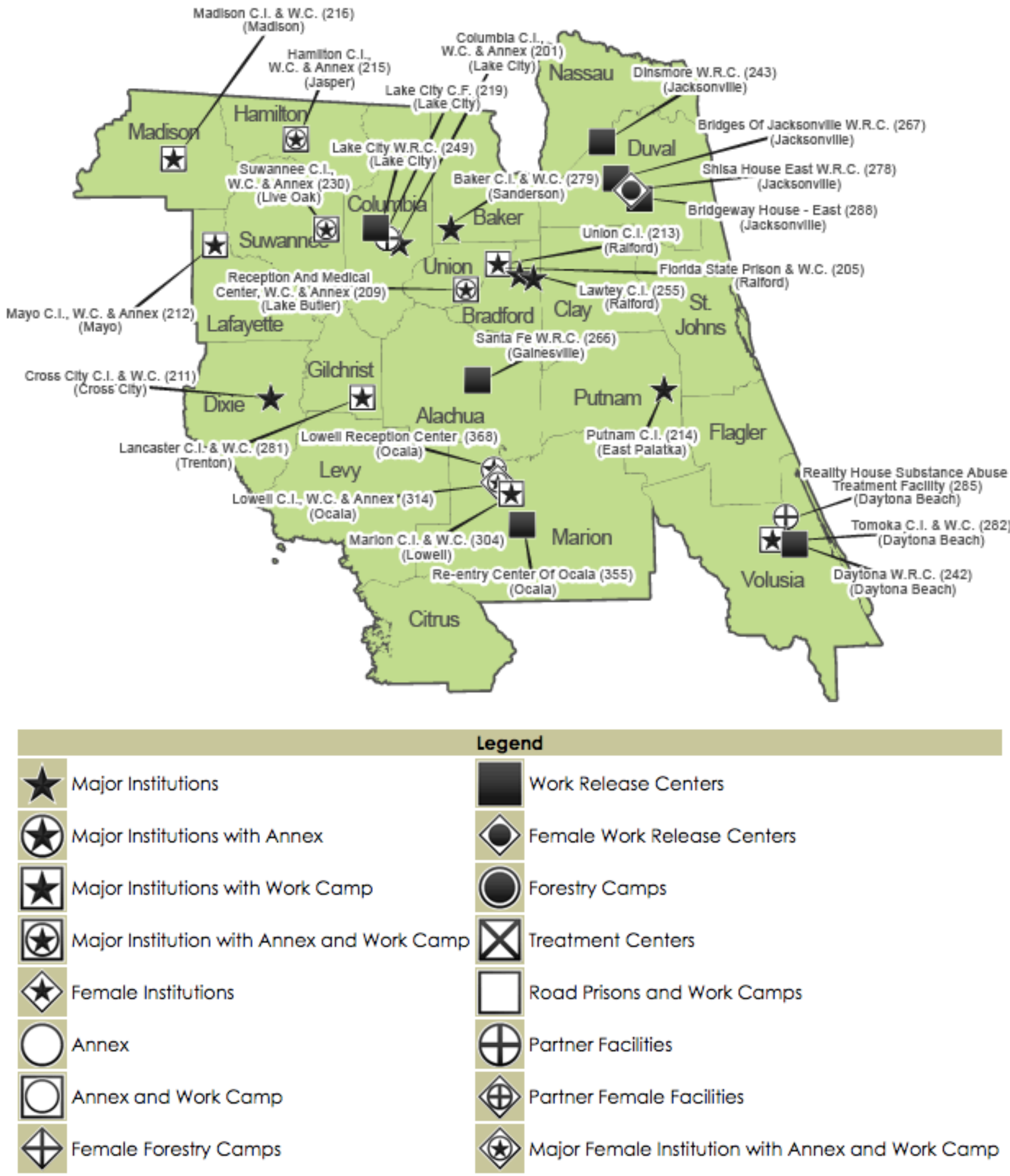
Within each region, there are several FDOC facilities of different types ranging from work camps to maximum-security prisons depending on the facility and region. A detailed map of the North Florida region, Region 1, including a legend, is shown in Figure 4.2. Region 1 includes 29 FDOC facilities with 15 major prisons located in this region. Figure 4.3 presents a detailed map of Region 2, which includes 26 FDOC facilities and 17 major prisons located in Central Florida. The detailed map of Region 3, South Florida, is presented in Figure 4.4. Region 3 includes 46 FDOC facilities, with 16 major prisons. Although the number of institutions is relatively evenly distributed across regions, the distribution of inmates is not.

Figure 4.2: Detailed Map of FDOC Region 1 with Legend.



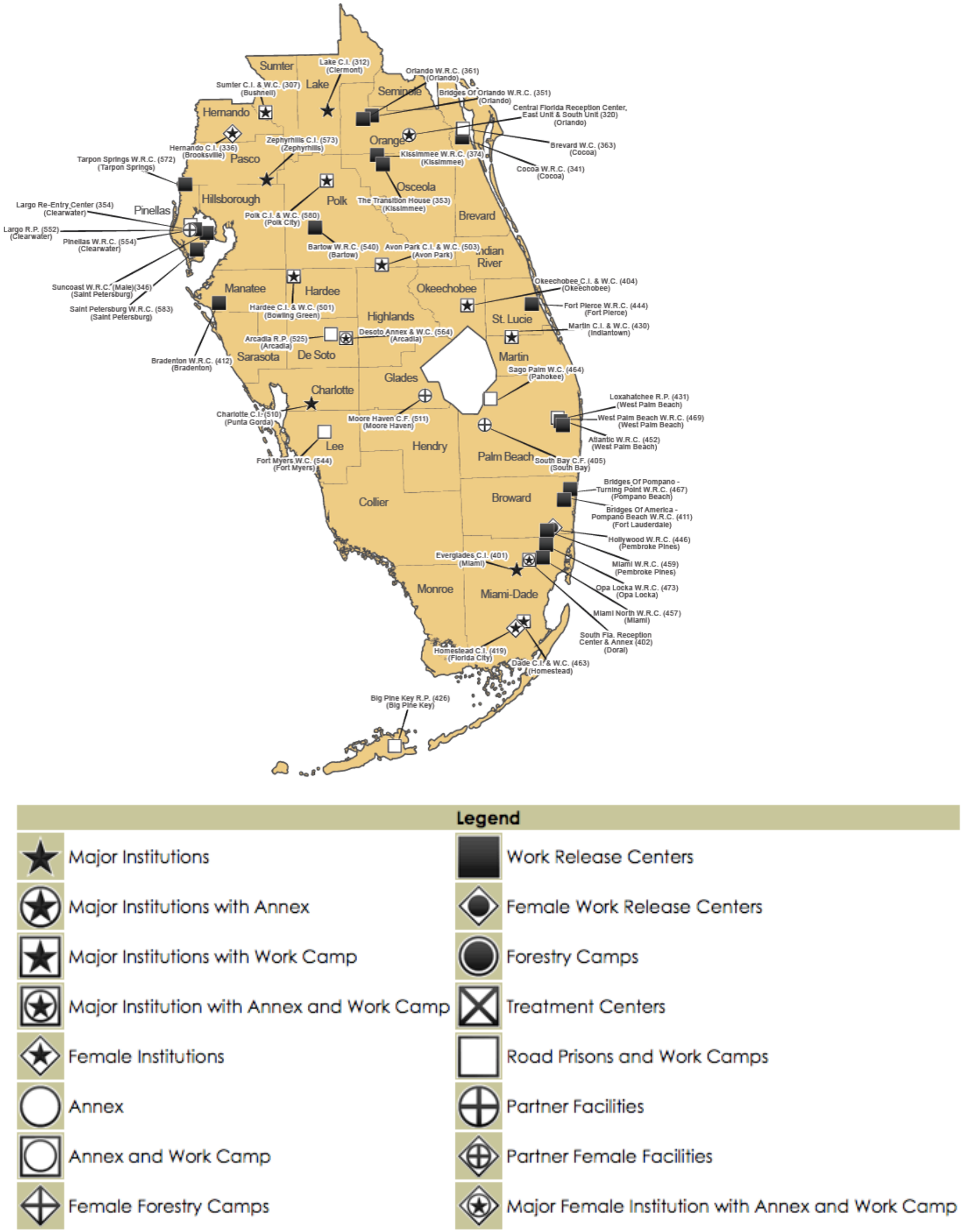
Source: FDOC, October 2014

Figure 4.3: Detailed map of FDOC Region 2 with Legend.



Source: FDOC, October 2014

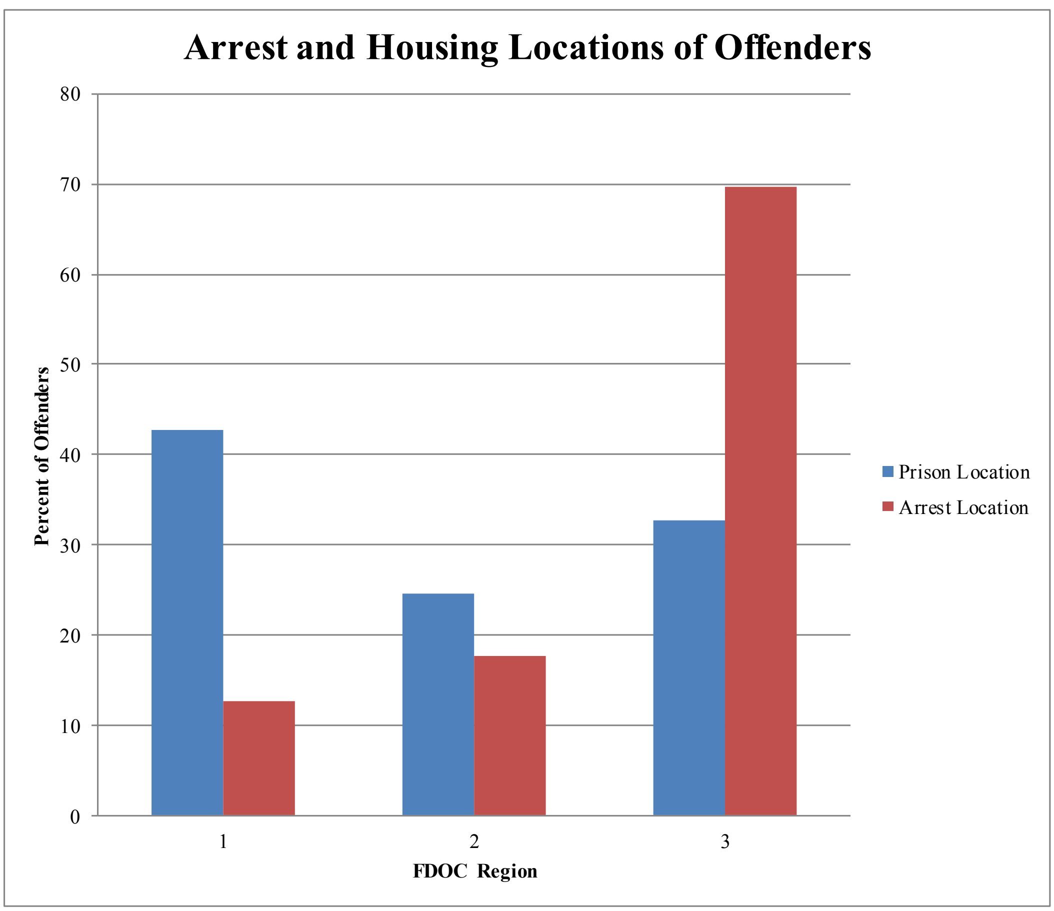
Figure 4.4: Detailed map of FDOC Region 3 with Legend.



Source: FDOC, October 2014

Figure 4.5 presents a breakdown of offenders based on the county of their arrest and the location of the prison where they served time for that offense. Roughly 43% of offenders served time in a facility located in Region 1, but only 13% of offenders were arrested for crimes committed in Region 1. Region 2 is more evenly distributed across these dimensions, with 25% of offenders housed in Region 2 and 18% arrested in Region 2. Region 3 presents the largest spatial mismatch between arrest location and facility with 70% of offenders arrested in the region, and only 33% housed in the region. This figure shows that the majority of offenders in Florida are arrested in the South Florida region yet serve time in the North Florida Region.

Figure 4.5: Offender Arrest and Housing Locations by Region.



This spatial mismatch between an inmate's institutional location and their home has potentially important implications for offenders upon release. As distance from home increases, so too do transportation costs for family and friends of the offender. As transportation costs increase, the likelihood of visitation decreases. Decreases in visitations have the potential to either positively or negatively affect recidivism in the future.

4.3 Previous Literature

Broadly speaking, visitation while incarcerated may be beneficial to inmates as it allows for the maintenance of social ties to family and friends outside of prison. Evidence suggests that inmates who receive visitors may better transition back into society post-release due to connections to employment and living situations (Liu et al., 2014). However, the mechanism through which recidivism risk is affected may be dependent on the relationship between the inmate and visitor.

Visits from family members such as parents or spouses have been found to have the largest impact on decreasing recidivism risk in the future. Studies examining why visits from family are relatively important to reducing future criminal behavior find a positive relationship between family visits and the probability of obtaining employment post release (Liu et al., 2004; Berg and Huebner, 2011; Duwe and Clark, 2011). Employment post release has been shown to reduce recidivism risk (Freeman, 2003; Liu et al, 2004; Tahmincioglu, 2010; Berg and Huebner, 2011; Duwe and Clark, 2011; Husock, 2012, Pia Negro, 2012; Rosenberg, 2012). While family visits overall are potentially beneficial, visits from ex-spouses close to release have been shown to increase the risk of reconviction in the future (Duwe and Clark, 2011). This finding suggests that the relationship between the inmate and the visitor may determine whether visits are beneficial.

Visits from friends of the inmate have the potential to shape their perception of how their incarceration has affected others. Liu et al. (2014) find that inmates who are frequently visited by friends are more likely to believe their incarceration has been difficult on others than inmates whose friends do not visit, or visit less frequently. Additionally, offenders who believe their prison spell was difficult for loved ones are less likely to reoffend in the future.

These previous studies suggest that when visitations do occur they have the potential to decrease future criminal activity, depending on the relationship between the inmate and the visitor. However, not all inmates receive visits while incarcerated. Duwe and Clark (2011) report that 39% of inmates are never visited during incarceration. A variety of factors, including individual characteristics, may affect whether or not an inmate receives visitors while serving time. A main barrier to visitation reported by relatives and friends of prisoners is the cost of transportation to the prison (Bedard and Helland, 2004).

Prisoners housed in isolated prison locations are less likely to receive visitors and thus less likely to internalize the effects of visitation while incarcerated (Bedard and Helland, 2004). The potential effects of serving time with infrequent visitations on an inmate's social connections are well documented within the literature. However, the relationship between distance and crime has received far less attention. Bedard and Helland (2004) use natural variation in the expansion of women's prisons to examine the effects of prison isolation on female crime rates. Their results suggest that an increase the expected distance between residence and incarceration facility causes a decrease in the female crime rate. This evidence of the deterrent effect of prison isolation is in line with Becker's (1968) theory of the economics of crime.

This deterrence argument rests on the assumption that distance and visitation are negatively related and that a lack of visitation is punitive in nature. In order to justify these assumptions, Bedard and Helland (2004) compile data from the Bureau of Justice Statistics' Survey of Inmates (1997) and show that female inmates incarcerated more than 50 miles from their residence at the time of arrest, are less likely to receive visits or phone calls while serving time. Furthermore, evidence suggests that prison visitation may be prohibitively costly due to high transportation costs.

Given that distance and visitation are related, how does a lack of visitation affect the inmate, and should this be considered a component of the harshness of incarceration? Becker's (1973) economic theory of the household includes time spent with children as a utility producing consumption good for parents. Bedard and Helland (2004) extend this consumption component to all individuals, including those serving time. This suggests that a lack of visitation while incarcerated deprives inmates of the utility gained from spending time with loved ones. As a result, they conclude the geographic isolation of a prison is a punitive measure.

Their analysis focuses specifically on female offenders and finds that geographic prison isolation has a deterrent effect on crimes committed by women. The mechanism with which this deterrence operates is the threat of forgone utility from the lack of visitation from family and friends. It follows from this line of reasoning that men should also be affected by distance between prison and home, as they too gain utility from visitation.

In this paper, I expand Bedard and Helland's (2004) study and examine whether the experience of serving time in a geographically isolated prison locations deters future crimes. If what deters female offenders from committing crimes is the inability to 'consume' the utility from visitation, then male offenders should also value this forgone consumption and respond accordingly. Using a survival model, I test whether a relationship exists between prison to residence distance and the timing and occurrence of recidivism.

4.4 Data and Empirical Approach

To examine this question, I use data from the Florida Department of Corrections (FDOC) Offender Based Information System (OBIS) in October 2013 and January 2015.[70] These open-records databases provide information on offenders within FDOC facilities.[71] From the October 2013 file, I create demographic, criminal history, and distance variables for Florida offenders who were not currently incarcerated in Florida during October 2013. The January 2015 information lists all inmates currently serving time in FDOC facilities in January 2015. Combining these databases allows me to calculate the occurrence and timing of recidivism for inmates who returned to prison by January 2015. Table 4.1 presents summary statistics of the variables included in this analysis.

[70] The October 2013 database was the earliest database I had access to at the start of this project. This database provides information on offenders who have passed through the FDOC system since 1997 but were not currently incarcerated as of October 2013.
[71] Only incarcerations in Florida prisons are included in this database.

Table 4.1: Summary Statistics.					
Variable	Observations	Mean	St. Dev.	Min	Max
Survival Indicators					
Survival	77202	0.931	0.253	0	1
Days until recidivism	5323	1346	1087	62	7736
Distance Indicators					
Distance (Release to Facility, mi)	77202	157.312	123.486	1.279	579.784
Demographic Controls					
Black	77202	0.575	0.494	0	1
Asian/Pacific Islander	77202	0.00004	0.006	0	1
Hispanic	77202	0.020	0.142	0	1
White	77202	0.402	0.490	0	1
American Indian	77202	0.0008	0.028	0	1
Age at release	77202	39.807	9.933	17.649	85.614
Gender	77202	0.914	0.280	0	1
Criminal Controls					
Violent offense in history	77202	0.330	0.470	0	1
Property offense in history	77202	0.484	0.500	0	1
Number of previous incarcerations	77202	3.276	1.777	1	16
Community custody level	77202	0.129	0.335	0	1
Minimum custody level	77202	0.270	0.444	0	1
Medium custody level	77702	0.405	0.491	0	1
Close custody level	77202	0.174	0.379	0	1
Maximum custody level	77202	0.00001	0.004	0	1
Visible Tattoo	51938	0.247	0.431	0	1

Prior to release, all inmates are required to create a release plan which includes an address at which they plan to reside once out of prison. This plan is updated up until the day the inmate is released from prison and is assumed to capture the location of an inmate's family and/or friends. To calculate a measure of distance between family and friends of an inmate and their incarceration location, I calculate the distance in miles between the release plan ZIP code and the ZIP code of the prison in which the inmate is serving time. The average distance between these locations is 157 miles. Previous work by Bedard and Helland (2004) and Drago et al. (2011) measures distance at the city level. An advantage to the FDOC data is the measurement of distance by ZIP codes. As ZIP codes are a more local level of analysis, the measure of distance I am able to construct is more precise than those used in previous studies.

In addition to the distance variable, I construct two variables measuring outcomes for released offenders. Survival indicates whether or not an inmate survived in society without being reincarcerated as of January 2015.[72] Survival equals zero if an inmate was incarcerated as of January 2015, and equals 1otheriwse. 93% of offenders released as of October 2013 have yet to return to incarceration in Florida as of January 2015, while 7% of those released offenders are currently incarcerated. I also calculate a variable which measures differences in timing of these returns to prison. On average, an offender survives 1,346 days (3.7 years) before returning to prison. The timing of reincarceration is important as differences in timing convey differences in offender characteristics related to recidivism. Analyses which using binary indicators of recidivism may miss important information conveyed by differences in timing.

To control for demographic characteristics that may affect recidivism, I construct dummy variables for race and gender and calculate the age at release for each inmate.[73] The sample of offenders included within this analysis is roughly 58% black, 40% white, 91% male, and has an average age of 40 years old. I also control for criminal history factors which may affect

---

[72] This is typically referred to as 'failure', where failure equals 1 if an inmate returned to prison. In order to be consistent across OLS and survival model results, I measure survival rather than failure. The survival rate is equal to one minus the failure rate.

[73] The following studies suggest these demographic factors affect recidivism: Jurik, 1983; Blumstein et al., 1987; Beck and Shipley, 1987; Visher and Linster, 1990; Anderson et al., 1991; Visher et al., 1991; Helpburn and Albonetti, 1994; Gendreau et al., 1996; Baumer, 1997; Beck and Shipley 1997; Hanley and Latessa, 1997; Benedict et al, 1998; Gainey et al., 2000; Kruttschnitt et al., 2000; Uggen, 2000; Benda and Toombs, 2002; Langan and Levin, 2002; Spohn and Holleran, 2002; Langan et al., 2003; Kubrin and Stewart, 2006; Windzio, 2006; Bales and Mears, 2008; Duwe and Donnay, 2008; Kohl et al., 2008; Lozano et al., 2010, and Waters, 2012.

recidivism. These include dummy variables for previous violent or property offenses in an inmate's history[74], custody levels, visible tattoos, and the number of times an inmate has been previously incarcerated.[75] Within my sample, roughly 33% of inmates served time for a violent crime, 48% for a property crime, the average number of previous incarcerations is 3, and about 40% of inmates are housed in medium custody.

To examine whether distance between residence and prison is related to recidivism, I begin by estimating the following OLS regression:

$$Survival_i = \beta_1 distance_i + \beta_i(X_i) + \gamma_i + \delta_i + \varepsilon_i \qquad (1)$$

Where $Survival_i$ is a dummy variable which equals 0 if offender i is incarcerated as of January 2015, and 1 otherwise. $Distance_i$ measures the distance in miles between offender i's release plan residence and the prison where they were most recently incarcerated. X_i is a set of demographic and criminal history control variables which may affect the likelihood of survival. County fixed effects are represented by γ_i and control for factors specific to the county offender i was arrested in which may affect the survival rate.[76] δ_i indicates a prison-level fixed effect to control for facility specific attributes that may affect the likelihood of survival for offender i.

When examining recidivism it is important to take into account not only the occurrence of a return to prison, but also the timing of that occurrence. Differences in timing reflect

[74] Violent and property crime dummy variables are calculated using FBI definitions of violent and property crimes.
[75] I can only measure incarcerations within Florida prisons given the nature of the data.
[76] For example, perhaps Miami-Dade County is especially efficient at incarcerating offenders. The county fixed effect controls for differences across counties related to recidivism.

differences in costs to the correctional system. Additionally, using only binary indicators to measure recidivism treats an offender who returned to prison after one month the same as an offender who survived several years before reincarceration. In order to properly account for the differences in timing of imprisonment across inmates, I utilize a survival analysis framework. I define survival length as the number of days between inmate i's most recent release and their next receipt into prison. The general survival function of inmate i can be represented by the following equation:

$$S_i = \exp\left[-\int_0^t h(T; x_i\gamma)dT \right] \quad (2)$$

Where S_i represents the number of days inmate i survives in society without experiencing a return to prison. $h(.)$ indicates the hazard rate of reincarceration, which is a function of variables which may affect recidivism, given by x_i with the coefficient vector γ, and the current and total time periods included in the analysis, represented by t and T respectively.

To estimate the hazard rate for survival within my analysis, I use a log-logistic distribution for the starting hazard. This flexible functional form allows for non-monotonic hazard functions. The modified log-logistic hazard function is shown in equation 3.

$$h(t; x_i\gamma) = \frac{[\exp(x_i\gamma)\lambda t^{\lambda-1}]}{[1+\exp(x_i\gamma)t^{\lambda}]} \quad (3)$$

Where λ describes the relationship between the hazard and duration. In the log-logistic distribution, $\lambda < 1$ indicates declining hazard over time, and $\lambda > 1$ indicates a hazard rate which increases then falls.

4.5 Results

OLS

I begin by examining the relationship between distance and survival using OLS. In these regressions, the dependent variable is an indicator which equals 1 if the offender was actively incarcerated as of January 2015, and equals 0 otherwise. Table 4.2 presents the regression results examining the relationship between survival and distance. Column (1) presents results including control variables, and column (2) adds the inclusion of county and prison-level fixed effects.

Table 4.2: Relationship between Distance and Survival Indicator.

	(1)	(2)
Distance from Prison to Residence	0.000***	0.000***
	(0.000)	(0.000)
Black	-0.077***	-0.083***
	(0.011)	(0.011)
Asian/Pacific Islander	0.009	-0.012
	(0.013)	(0.023)
Hispanic	-0.064***	-0.073***
	(0.013)	(0.013)
White	-0.074***	-0.076***
	(0.011)	(0.011)
American Indian	-0.055	-0.058
	(0.035)	(0.037)
Age at release	0.002***	0.002***
	(0.000)	(0.000)
Gender	-0.009**	-0.023**
	(0.004)	(0.012)
Visible Tattoo (face, head, neck, hands)	-0.029***	-0.026***
	(0.003)	(0.003)
Violent offense in history	0.010***	0.007**
	(0.003)	(0.003)
Property offense in history	-0.009***	-0.012***
	(0.003)	(0.003)
Number of previous incarcerations	-0.010***	-0.010***
	(0.001)	(0.001)
Community custody level	0.021**	0.002
	(0.009)	(0.011)
Minimum custody level	0.007	-0.000
	(0.009)	(0.010)
Medium custody level	0.005	-0.000
	(0.009)	(0.010)
Close custody level	0.005	-0.000
	(0.009)	(0.010)
Fixed Effects	No	Yes
Observations	51,938	51,938

Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating p<0.01, p<0.05, and p<0.1 respectively. The dependent variable in this analysis =1 if an offender had not returned to prison in Florida as of January 2015. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed. Facility fixed effects are also included and control for prison-specific effects that may affect the likelihood of survival post-release.

Both specifications suggest a positive and significant relationship exists between distance and the probability of survival outside of prison, however the magnitude on this effect is very small. All of the control variables included within the analysis follow the expected signs with the exception of the violent dummy variable indicating whether an inmate has a violent offense in their history.[77] Race, gender (male=1), previous property offenses, previous incarcerations, and visible tattoos all show evidence of a negative relationship with survival. Additionally, as age increases so too does the probability of survival.

The OLS analysis is limited in its ability to capture differences across inmates conveyed by differences in timing between prison spells. It is important to account for the timing of recidivism as differences in timing convey differences in unobservable inmate characteristics as well as costs paid by the correctional system. To account for these differences in timing, a survival model is used in the second portion of the analysis.

SURVIVAL MODEL

Survival models utilize a two-part dependent variable to account for whether or not failure takes place as well as differences in timing until failure for each subject. In the context of this study, the dependent variable includes a dummy variable for whether or not an offender returned to prison as well as the number of days between release from prison and reincarceration. Survival analysis adds an additional dimension to analyses of recidivism as differences in days survived in society are accounted for.

The results from the survival analysis are presented in Table 4.3. Column 1 presents results for the relationship between the likelihood of survival and distance, with the inclusion of

[77] The result for violent offenders suggests that increases in distance are associated with increases in the expected probability of survival outside of prison. It is possible that being farther away from family and friends is more beneficial to a violent offender's reform than criminals with other previous offense types.

control variables. Column 2 again expands on column 1 with county and prison-level fixed effects. For ease of interpretation, results are presented in time ratio format. Time ratio coefficients indicate how estimated survival length is affected by a one unit change in a given independent variable, where time ratios greater than one indicate increases in estimated survival length equal to the coefficient minus one.

Table 4.3: Loglogisitc Survival Regression Results for the Relationship between Distance and Survival, Time Ratios Presented.

	(1)	(2)
Distance from Prison to Residence	1.001***	1.001***
	(0.000)	(0.000)
Black	0.013**	0.011**
	(0.025)	(0.021)
Asian/Pacific Islander	2.160***	0.000***
	(0.000)	(0.000)
Hispanic	0.019**	0.015**
	(0.036)	(0.028)
White	0.015**	0.013**
	(0.027)	(0.025)
American Indian	0.025*	0.022*
	(0.056)	(0.050)
Age at release	1.063***	1.064***
	(0.004)	(0.005)
Gender	0.769*	0.456*
	(0.108)	(0.192)
Visible Tattoo (face, head, neck, hands)	0.485***	0.523***
	(0.034)	(0.037)
Violent offense in history	1.301***	1.187**
	(0.092)	(0.085)
Property offense in history	0.773***	0.706***
	(0.053)	(0.049)
Number of previous incarcerations	0.760***	0.756***
	(0.016)	(0.016)
Community custody level	1.904***	1.071
	(0.462)	(0.298)
Minimum custody level	1.181	0.972
	(0.267)	(0.246)
Medium custody level	1.130	0.987
	(0.250)	(0.244)
Close custody level	0.807	0.699
	(0.183)	(0.177)
Fixed Effects	No	Yes
Observations	51,938	51,938

Robust standard errors appear in parentheses. Significance is denoted by *** , **, and * indicating p<0.01, p<0.05, and p<0.1 respectively. . The dependent variable in this analysis is comprised of two parts, a dummy variable indicating whether or not an inmate had returned to prison in Florida as of January 2015, and a timing variable indicating the number of days an inmate 'survived' in society. County fixed effects control for unobservable differences across counties, such as differences in clearance rates. The county variable lists the county in which the most recent crime for each inmate was committed. Facility fixed effects are also included and control for prison-specific effects that may affect the likelihood of survival post-release.

Overall, the findings using the survival framework suggest a positive relationship exists between distance and expected survival time. Columns (1) and (2) both show that increases in distance are associated with increases in the number of days an inmate survives in society. This result is consistent with OLS results, which suggest that as the distance between an inmate's home and prison increases, they become less likely to return to prison. The control variables in this portion of the analysis again follow the expected signs with the exception of the dummy variable for violent offenders.

Time ratio coefficient values greater than one correspond to increases in expected survival times. The coefficient on the distance measure used within this analysis is 1.001 in the most complete specification of Table 4.3 Column 2. Given this coefficient is greater than one, it suggests that a one mile increase in distance is associated with a 0.1% increase in expected survival time. From that relationship, a one standard deviation increase in distance of 123.486 miles is associated with a 12.349% increase in expected survival time. The average offender included within the analysis survives in society 1,346 days (3.688 years). Thus, a one standard deviation increase in distance is associated with an increase in the average offender's expected survival time of 166 days.

The findings from both the OLS and survival models are consistent with the work of Bedard and Helland (2004) which found that more isolated prisons have a deterrent effect on crimes. Although their work was specific to women, the results from my analysis suggest that this deterrent effect may apply generally to offenders who have the experience of isolated incarceration. Given the mechanism behind the deterrent effect in Bedard and Helland (2004) was the forgone utility from the lack of visitation, it is unsurprising that both male and female offenders are affected by serving time in a geographically isolated prison.

Overall, the findings from these regressions suggest that distance and survival are positively related. The OLS results suggest that increases in distance are associated with increases in the likelihood of survival. The survival results show that increases in distance are also associated with increases in expected survival times of inmates.

4.6 Conclusions

In this paper, I examine how distance between an inmate's prison and residence affects recidivism upon release. I first present results from OLS regressions of the relationship between whether an inmate returns to prison and home to prison distance. However, when examining how distance relates to recidivism it is important to account for both the timing and occurrence of recidivism for several reasons. First, differences in the timing between prison spells indicate differences in costs paid by the criminal justice system to house inmates. Second, using only binary indicators to measure recidivism treats an offender who returns to prison shortly after release as identical to an offender who survives several years post-release without another prison sentence. I use a survival model in order to capture the information conveyed by differences in timing.

The results from the OLS regressions suggest that as distance between an inmate's residence and prison increases, so too does the probability of survival. However, using OLS does not account for the differences in timing between incarcerations across inmates. When using a survival framework, the results again suggest a positive relationship between distance and the likelihood of survival. The interpretation of the survival model time ratio coefficient can be expressed as a number of days. For every additional standard deviation increase in distance between prison and residence, the estimated number of days the average inmate survives in society increases by 166.

Previous research examining the role of geographic isolation of prison in future criminal behavior has conflicting results. Several studies find that allowing inmates to serve time closer to family reduces recidivism risk, as inmates are better able to maintain social ties while incarcerated (Bales and Mears, 2008; Duwe and Clark, 2011;, Liu et al., 2014). However, findings from Bedard and Helland (2004) suggest that a more isolated prison environment is a deterrent for female offenders. The results from my analysis are consistent with Bedard and Helland's (2004) finding that geographic prison isolation is positively related to the likelihood of survival post-release.

It should be noted that these results are meaningful if the release residence measure captures the residence location of an inmate's personal connections outside of prison. These personal connections are likely the individuals visiting the inmate while incarcerated. Future work should examine other measures of residence and distance to ensure the robustness of this finding. Additionally, these findings do not present causal impacts and rely on the extent to which prison assignment is random. Future analyses should take into account the process of prison placement for inmates in Florida.

Chapter 5

Summary and Conclusion

Government policy has long been used to try to improve the lives of citizens. Recently, two main areas of importance to policymakers have been improving economic opportunities in low-income areas and finding low-cost solutions to decrease crime. The essays in this dissertation discuss three policy-relevant topics within those fields. I contribute to the scholarly literature in the areas of each research chapter by providing empirical evidence of the effectiveness of policies and programs aimed at helping low-income communities and reducing criminal behavior.

Chapter 2 examines the effect of a specific federal tax credit program on attracting new businesses and employment to low-income communities. The NMTC program provides federal income tax credits to private investors willing to invest in projects in eligible low-income communities. Using data from the Dun and Bradstreet Marketplace files and the US Census, we examine whether this program attracted new businesses and employment to eligible census tracts. Since business owners choose where to locate, comparing the number of new businesses in eligible low-income communities to the number of new businesses in ineligible communities is likely to produce biased results. In order to avoid that potential endogeneity, we combine a difference-in-differences strategy with a regression discontinuity framework. This allows for the comparison of just eligible tracts to just ineligible tracts, before and after the program was implemented.

The results in Chapter 2 suggest that the NMTC was able to attract new businesses and employment to eligible census tracts. Looking at employment in new firms, we find an increase in new employment in just eligible tracts after the program was implemented. Similarly, when examining the number of new businesses after the NMTC began, our results show an increase in the number of new firms in just eligible tracts. However, the significance of these overall effects is not consistent across the eligibility ratio cutoff ranges considered. It is possible that differences in industry composition may be responsible for the differences in significance across years.

Previous research suggests that examining the overall effect of programs that subsidize capital or labor may miss important differences in underlying industry-specific effects. Hanson and Rohlin (2011b) develop a formal model of the relationship between labor subsidies and the location choices of labor-intensive and capital-intensive firms. The main implication of their model is that geographic areas where labor is subsidized are able to attract more labor-intensive industries, as businesses in those industries will be willing to bid more to locate in the subsidized areas.

Our research builds off of Hanson and Rohlin (2011b) and examines whether the NMTC attracts more new businesses in industries with higher capital start up costs. Although the NMTC is written such that it can be used for any purpose, in practice investors use it for capital-intensive projects. As such, we consider the NMTC to be a capital tax credit. When capital is subsidized, the price of capital in relation to labor also changes. Additionally, capital and labor tend to be highly substitutable and as a result it is possible that improvements in capital may substitute away increases in unskilled labor. McCulloch and Yellen (1979) formalize this relationship and find evidence that when capital becomes cheaper, capital-intensive firms may respond by improving capital at the expense of unskilled workers.

Our by industry results show that the NMTC attracted new businesses in several industries in eligible tracts. However, new employment only increased in the FIRE and services industries. This finding is consistent with findings from McCulloch and Yellen (1979), which argue that when capital is subsidized firms may choose to invest in capital at the expense of unskilled labor. It is unsurprising that FIRE and services still experience increases in employment after a capital subsidy. First, the FIRE industry typically does not consist of unskilled labor. As such, capital and labor are not likely highly substitutable in this industry. Second, capital has not become technologically advanced enough to be highly substitutable with labor in the services industry.

In Chapter 3, I examine the relationship between visible tattoos and recidivism. Potential employers may interpret visible tattoos as a signal of other unobservable characteristics. As such, visible tattoos may serve as a barrier to entering the labor force. Ex-offenders face many barriers to gaining employment post release. Additionally, ex-offenders are particularly important labor force participants as research suggests that employment plays an important role in reducing future criminal behavior. A large body of research has examined the factors that contribute to the likelihood of future criminal activity for repeat offenders. However, very few studies focus on the role that personal appearance may play in affecting the likelihood of future incarceration.

I contribute to a small but growing literature examining how visible tattoos, one aspect of an ex-offender's appearance, affect future criminal activity. Two recent criminology studies examine the relationship between tattoos and future criminal behavior. Lozano et al. (2010) consider three sample of individuals: inmates with prison tattoos, inmates with non-prison tattoos, and college students. Their findings suggest that inmates with tattoos are more likely to commit future crimes than inmates without prison tattoos and college students. Waters (2012) expands upon Lozano et al. (2010) and examines the relationship between visible tattoos and recidivism. His results suggest that inmates with visible tattoos are more likely to be reconvicted for new felony offenses and new violent offenses within three years.

In Chapter 3, I expand upon those previous studies by developing two measures of visibility and utilizing a survival model to take into account the timing and occurrence of criminal behavior. I utilize a log-logistic survival model to allow for a flexible hazard function. The results from the survival analysis suggest that inmates with highly visible tattoos return to prison faster and more often than inmates with other, less visible, tattoos. The most conservative estimate suggests that inmates with tattoos on their face, head, neck, or hands return to prison roughly 419 days sooner than inmates with tattoos on arms or legs.

The findings from this chapter have important policy implications. Some small scale reentry programs are teaching ex-offenders, in particular ex-gang members, how to use makeup to effectively cover visible tattoos. Additionally, a number of non-profit organizations are beginning to offer subsidized or free tattoo removal for criminals with visible tattoos. The findings from my analysis suggest that visible tattoos may play an important role in an ex-offender's ability to reenter society. Future research in this area should examine further the value of obtaining a tattoo removal, both to the individual and to tax payers.

Chapter 4 focuses on the relationship between prison isolation and recidivism. Specifically, I examine whether the distance between and offender's home and incarceration location is related to the timing and occurrence of recidivism in the future. Two competing theories on this relationship prevail in the literature. There are potential benefits of housing offenders close to home as they are better able to maintain social ties to family and friends while incarcerated. Research suggests this may be associated with better behavior inside prison, and an easier transition into legitimate employment post-release (Liu et al., 2004; Berg and Huebner, 2011; Duwe and Clark, 2011). Another area of research suggests however that harsh prison conditions may be a deterrent to crime for female offenders (Bedard and Helland, 2004). Specifically, as the expected distance between home and prison increases, the female crime rate within a city drops.

Using data from the Florida Department of Corrections Offender Based Information System (FDOC OBIS) database, I examine whether distance and recidivism are related. If the expectation of serving time far away is a deterrent for female offenders, does the experience of serving time far from home deter future crime from the individuals who experienced the isolation? The results from both survival and OLS estimations suggests that as distance between an offender's home and prison increases, the likelihood they will return to prison in the future decreases.

Again the findings from this analysis have important policy implications. Department of Corrections official are faced with limited budgets and housing options. If inmates housed farther away from home are deterred from committing future crimes based on that experience, then housing offenders far from home may have the potential to reduce crime rates and costs in the future. Additionally, decisions about technology based visitation systems (i.e. Skype) for inmates housed farther from home should take these results into account.

References

Anderson, D. B., Schumacker, R. E. & Anderson, S. L. 1991. "Release Characteristics and Parole Success." *Journal of Offender Rehabilitation* 17:133-145.

Arauzo-Carod, Josep-Maria, Daniel Liviano-Solis, and Miguel Manjon-Antolin. 2010. "Empirical Studies in Industrial Location: An Assessment of their Methods and Results." *Journal of Regional Science*, 50(3), 685-711.

Arzaghi, Muhammad and J.V. Henderson. 2008. "Networking off Madison Avenue." *Review of Economic Studies*, 75(4), 1011-1038.

Bales, W. D. & Mears, D.P. 2008. "Inmate Social Ties and the Transition to Society: Does Visitation Reduce Recidivism?" *Journal of Research in Crime and Delinquency* 20:1 35.

Baumer, E. 1997. "Levels and Predictors of Recidivism: The Malta Experience." *Criminology* 35(4), 601-628.

Beck, A.J., and Shipley, B.E. 1989. "Recidivism of Prisoners Released in 1983." *Bureau of Justice Statistics—Special Report.* Washington, DC: U.S. Department of Justice.

Beck, Allen J. & Bernard E. Shipley. 1987. "Recidivism of Young Parolees." *Bureau of Justice Statistics—Special Report.* Washington, DC: U.S. Department of Justice.

Beck, Allen J. & Bernard E. Shipley. 1997. "Recidivism of Prisoners Released in 1983." *Bureau of Justice Statistics—Special Report.* Washington, DC: U.S. Department of Justice.

Becker, G.S. 1968. "Crime and Punishment: An economic approach." *Journal of Political Economy,* 76:169-217.

Becker, G.S. 1973. "A Theory of Marriage: Part I". *Journal of Political Economy,* 81(4): 813-848.

Bedard, K., and Helland, E. 2004. "The Location of Women's Prisons and the Deterrence Effect of "Harder" Time". *International Review of Law and Economics* 24: 147-167.

Benda, B. B. & Toombs, N. J. 2002. "Two Preeminent Theoretical Models: A Proportional Hazard Rate Analysis of Recidivism." *Journal of Criminal Justice* 30, 217-228.

Benedict, R. W., Huff-Corzine, L., & Corzine, J. 1998. "Clean Up and Go Straight: Effects of Drug Treatment on Recidivism among Felony Probationers." *American Journal of Criminal Justice,* 22, 169-187.

Black, Sandra. 1999. "Do Better Schools Matter? Parental Valuation of Elementary Education." *Quarterly Journal of Economics*, 114(2), 577-599.

Blumstein, A., Barnett, A., & Farrington, D. 1987. "Probabilistic Models of Youthful Criminal Careers." *Criminology*, 25, 83-107.

Bruce, Donald and John Deskins. 2012. "Can State Tax Policies be used to Promote Entrepreneurial Activity?" *Small Business Economics*, 38, 375-397.

Bureau of Labor Statistics. 2015. "Entrepreneurship and the US Economy: Chart 3. Survival rates of establishments, by year started and number of years since starting, 1994–2010, in percent". http://www.bls.gov/bdm/entrepreneurship/bdm_chart3.htm

Busso, Matias, Jesse Gregory, and Patrick Kline (2013). "Assessing the Incidence and Efficiency of a Prominent Place Based Policy." *American Economic Review*, 103(2), 897-947.

Carson, E.A., Sabol, W.J. 2011. "Prisoners in 2011." *Bureau of Justice Statistics.* Washington, D.C.: U.S. Department of Justice.

Chen, K. & Shapiro, J. 2007. "Do Harsher Prison Conditions Reduce Recidivism? A Discontinuity-based Approach." *American Law and Economics Review,* 9(1), 1-29.

Crowe, M. 2012, September 20. "Are Tattoos in the Workplace Still Taboo?" *USA Today.*

Dooley, B., Seals, A., Skarbek, D. 2013. "The Effect of Prison Gang Membership on Recidivism." *Journal of Criminal Justice*, 42(3), 267-275.

Drago, F., Galbiati, R., and Vertova, P. 2011. "Prison Conditions and Recidivism". *American Law and Economics Review* 13: 103-130.

Duranton, Gilles and Diego Puga. 2004. "Micro-foundations of urban agglomeration economies." in J. Vernon Henderson and Jacques-Francois Thisse (eds.), *Handbook of Urban and Regional Economics, Volume 4*, Elsevier B.V. North Holland, Amsterdam, 2063-2118.

Duranton, Gilles, Laurent Gobillon, and Henry Overman. 2011. "Assessing the Effects of Local Taxation Using Microgeographic Data." *Economic Journal* 121(555), 1017-1046.

Duwe, G. & Donnay, W. 2008. "The Impact of Megan's Law on Sex Offender Recidivism: The Minnesota Experience." *Criminology,* 46(2), 411-446.

Duwe, G. and Clark, V. 2011, "Blessed Be the Social Tie That Binds: The effects of prison visitation on recidivism." *Criminal Justice Policy Review.*

Florida Department of Corrections (FDOC). 2013. "Florida Prison Recidivism Report: Releases from 2004 to 2011." *FDOC Publications.*

Freedman, Matthew. 2012. "Teaching New Markets Old Tricks: The Effects of Subsidized Investment on Low-Income Neighborhoods." *Journal of Public Economics* 96(11-12): 1000-1014.

Freedman, Matthew. 2013. "Place-Based Programs and the Geographic Dispersion of Employment." *Working Paper*.

Freeman, R. 2003. "Can We Close the Revolving Door?: Recidivism vs. Employment of Ex-Offenders in the U.S." *Urban Institute Reentry Roundtable*.

Gabe, Todd M. and Kathleen Bell. 2004. "Tradeoffs between Local Taxes and Government Spending as Determinants of Business Location." *Journal of Regional Science*, 44(1), 21-41.

Gainey, R.R., Payne, B.K., & O'Toole, M. 2000. "The relationships between time in jail, time on electronic monitoring, and recidivism: An event history analysis of a jail based program." *Justice Quarterly,* 17(4), 733-752.

Gambetta, D. 2009. Codes of the Underworld: How Criminals Communicate. Princeton University Press.

Gendreau, P., Little, T., & Claire Goggin. 1996. "A Meta-Analysis of the Predictors of Adult Offender Recidivism: What Works?" *Criminology* 34: 575-607.

Glaeser, Edward. 2001. "The Economics of Location Based Tax Incentives." Harvard Institute of Economic Research Discussion Paper 1932.

Gruenewald, P.J. & West, B.R. 1989. "Survival Models of Recidivism Among Juvenile Delinquents." *Journal of Quantitative Criminology,* 5(3), 215- 229.

Gurley-Calvez, Tami, Thomas Gilbert, Katherine Harper, Donald Marples, and Kevin Daly. 2009. "Do Tax Incentives Affect Investment: An Analysis of the New Markets Tax Credit." *Public Finance Review* 37(4): 371-398.

Haltiwanger, John C., Ron S. Jarmin, and Javier Miranda (*forthcoming*). "Who Creates Jobs? Small vs. Large vs. Young." *The Review of Economics and Statistics*.

Hanley, D.E. & Latessa, E.J. 1997. "Correlates of Recidivism: The Gender Division." *Academy of Criminal Justice Sciences.*

Hanson, Andrew. 2009. "Local Employment, Poverty, and Property Value Effects of Geographically Targeted Tax Incentives: An Instrumental Variables Approach." *Regional Science and Urban Economics*, 39, 721-731.

Hanson, Andrew and Shawn M. Rohlin. 2011a. "Do Location-Based Tax Incentives Attract New Business Establishments?" *Journal of Regional Science*, 51(3), 427-449.

Hanson, Andrew and Shawn M. Rohlin. 2011b. "The Effect of Location Based Tax Incentives on Establishment Location and Employment across Industry Sectors." *Public Finance Review*, 39(2), 195-225.

Hanson, Andrew and Shawn M. Rohlin. 2013. "Do Spatially Targeted Redevelopment Programs Spill-Over?" *Regional Science and Urban Economics*, 43(1), 86-100.

Hennessey, R. 2013, February 27. "Tattoos No Longer A Kiss of Death in the Workplace." *Forbes*.

Hepburn, J. R. & Albonetti, C.A. 1994. "Recidivism among Drug Offenders: A Survival Analysis of the Effects of Offender Characteristics, Type of Offense, and Two Types of Intervention." *Journal of Quantitative Criminology* 10:159-179.

Hicks, Michael J. and Dagney Faulk. 2012. "The Effect of State-Level Add-On Legislation to the Federal New Market Tax Credit Program." *Ball State University Center for Business and Economic Research*.

Holmes, Thomas J. 1998. "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders." *Journal of Political Economy*, 106 (4), 667-705.

Husock, H. 2012, August 3. "From Prison to a Paycheck." *The Wall Street Journal.*

Jurik, N. C. 1983. "The Economics of Female Recidivism." *Criminology*, 21, 603-622.

Kaufman, J. 2013, April 17. "Keeping Their Art to Themselves." *The New York Times.*

Kilgannon, C. 2009, April 1. "When Tattoos Hurt Job Prospects." *The New York Times*.

Kling, J. 2006. "Incarceration Length, Employment, and Earnings." *American Economic Review*, 96(3): 863-876.

Kohl, R., Hoover, H.M., McDonald, S.M. & Solomon, A.L. 2008. "Massachusetts Recidivism Study: A Closer Look at Releases and Returns to Prison." *Urban Institute-Justice Policy Center*: Washington D.C.

Kolko, Jed. 2012. "Broadband and Local Growth." *Journal of Urban Economics*, 71(1), 100-113.

Kolko, Jed and David Neumark. 2008. "Changes in the Location of Employment and Ownership: Evidence from California." *Journal of Regional Science*, 48(4), 717-743.

Kolko, Jed and David Neumark. 2010. "Do enterprise zones create jobs? Evidence from California's enterprise zone program" *Journal of Urban Economics*, 68(1), 1-19.

Krupta, Douglas and Douglas Noonan. 2009. "Empowerment Zones, Neighborhood Change, and Owner Occupied Housing." *Regional Science and Urban Economics*, 39, 386-396.

Kruttschnitt, C., Uggen, C., & Shelton, K. 2000. "Predictors of Desistance Among Sex Offenders: The Interaction of Formal and Informal Social Controls." *Justice Quarterly*, 17, 61-87.

Kubrin, C.E. & Stewart, E.A. 2006. "Predicting Who Reoffends: The Neglected Role of Neighborhood Context in Recidivism Studies." *Criminology* 44:165-197.

Langan, P.A., and Levin, D.J. 2002. "Recidivism of Prisoners Released in 1994." *Bureau of Justice Statistics.* Washington, D.C.: Bureau of Justice Statistics.

Langan, P.A., Schmitt, E.L. & Durose, M.R. 2003. "Recidivism of Sex Offenders Released from Prison in 1994." *Bureau of Justice Statistics*. Washington, DC: U.S. Department of Justice.

Levitt, Steven D. 1998. "Juvenile Crime and Punishment." *Journal of Political Economy*, 106, 1156-1185.

Liu, S., Pickett, J.T., and Baker, T. 2014. "Inside the Black Box: Prison visitation, the Costs of Offending, and Inmate Social Capital". *Criminal Justice Policy Review,* 13: 1-25.

Lozano, A.T.R., Morgan, R.D., Murray, D.D., & Verghese, F. 2010. "Prison Tattoos as a Reflection of the Criminal Lifestyle." *International Journal of Offender Therapy and Comparative Criminology* 55 (4), 509-529.

McCulloch, Rachel and Janet L. Yellen. 1977. "Factor Mobility, Regional Development, and the Distribution of Income." *Journal of Political Economy*, 85(1), 79-96.

Neumark, David, Brandon Wall, and Junfu Zhang. 2011. "Do Small Businesses Create More Jobs? New Evidence for the United States from the National Establishment Time Series." *The Review of Economic and Statistics*, 93(1), pp. 16-29.

Neumark, David, Junfu Zhang, and Brandon Wall. 2007. "Employment Dynamics and Business Relocation: New Evidence from the National Longitudinal Establishment Time Series." *Research in Labor Economics*, 26, pp. 39-83.

Oakley, Deirdre and Hui-Shien Tsao. 2006. "A New Way of Revitalizing Distressed Urban Communities? Assessing the Impact of the Federal Employment Zone Program." *Journal of Urban Affairs*, 25, 443-471.

Patrick, Carlianne. 2013. "Jobless Capital? The Role of Capital Subsidies." *Mimeo*.

Patrick, Carlianne (forthcoming). "Does Increasing Available Non-Tax Economic Development Incentives Result in More Jobs?" *National Tax Journal*.

Patridge, Mark D., Dan S. Rickman, and Hui Li. 2009. "Who Wins from Local Economic Development? A Supply Decomposition of U.S. County Employment Growth." *Economic Development Quarterly*, 23(1): 13-27.

Pew Center on the States. 2010. "Millennials: Confident. Connected. Open to Change." *Pew Center on the States.*

Pia Negro, M. 2012, October 16. "Baltimore Program Provides Job Support for Ex-Prisoners Coming Home." *Baltimore News.*

Putnins, A. 2002. "Young Offenders, Tattoos and Recidivism." *Psychiatry, Psychology and Law,* 9(1), 62-68.

Rathelot, Roland and Patrick Sillard. 2008. "The Importance of Local Corporate Taxes in Business Location Decisions: Evidence from French Micro Data." *Economic Journal*, 118, 499-514.

Rohlin, Shawn M. and Amanda Ross. 2015. "Does Bankruptcy Law Affect Business Turnover? Evidence from New and Existing Businesses." *Forthcoming at Economic Inquiry.*

Rohlin, Shawn M., Stuart S. Rosenthal, and Amanda Ross. 2014. "Tax Avoidance and Business Location in a State Border Model." *Journal of Urban Economics*, 83, 34-49.

Rosenberg, T. 2012, March 28. "Out of Jail, and Into a Job." *The New York Times*.

Rosenthal, Stuart S. and Amanda Ross. 2010. "Violent Crime, Entrepreneurship, and Cities." *Journal of Urban Economics*, 67(1), 135-149.

Rosenthal, Stuart S. and William C. Strange. 2001. "The Determinants of Agglomeration." *Journal of Urban Economics*, 50(2), 191-229.

Rosenthal, Stuart S. and William C. Strange. 2003. "Geography, Industrial Organization, and Agglomeration." *The Review of Economics and Statistics*, 85 (2): 377-393.

Rosenthal, Stuart S., and William C. Strange. 2005. "The Geography of Entrepreneurship in the New York Metropolitan Area." *Economic Policy Review*, (Special Issue on "Urban Dynamics in New York City"). New York Federal Reserve Bank, December, 11(2), 29-54.

Rubin, Julia, and Gregory Stankiewicz. 2005. "The New Markets Tax Credit Program: A Midcourse Assessment." *Community Development Investment Review* 1(1): 1-11.

Rupasingha, Anil and Stephen J. Goetz. 2013. "Self-Employment and Local Employment Performance: Evidence from US Counties." *Papers in Regional Science*, 92, 141-161.

Spohn, C. & Holleran, D. 2002. “The Effect of Imprisonment on Recidivism Rates of Felony Offenders: A Focus on Drug Offenders.” *Criminology* 40:329-358

Stephens, Heather M. and Mark D. Partridge. 2011. “Do Entrepreneurs Enhance Economic Growth in Lagging Regions?” *Growth and Change*, 42(4), 431-465.

Stephens, Heather M., Mark D. Partridge, and Alessandra Faggian. 2013. “Innovation, Entrepreneurship, and Economic Growth in Lagging Regions.” *Journal of Regional Science*, 53(5), 778-812.

Tahmincioglu, E. 2010, February 17. “Unable to get Jobs, Freed Inmates Return to Jail.” *NBC News*.

The Sentencing Project. 2009. “Incarcerated Parents and Their Children: Trends 1991-2007”.

Uggen, C. 2000. “Work as a Turning Point in the Life Course of Criminals: A Duration Model of Age, Employment, and Recidivism.” *American Sociological Review* 67, 529-546.

Visher, C.A. & Linster, R.L. 1990. “A Survival Model of Pretrail Failure.” *Journal of Quantitative Criminology*, 6(2), 153-184.

Visher, C.A., Lattimore, P.K., & Linster, R.L. 1991. “Predicting the Recidivism of Serious Youthful Offenders Using Survival Models.” *Criminology*, 29(3), 329-366.

Waters, K. 2012. “The Tattooed Inmate and Recidivism.” *Electronic Theses, Treatises, and Dissertations*. Paper 5262.

Windzio, M. 2006. “Is There a Deterrent Effect of Pains of Imprisonment? The Impact of ‘Social Costs’ of First Incarceration on the Hazard Rate of Recidivism.” *Punishment and Society,* 8(3), 341-364.

Kaitlyn R. Harger
Ph.D. Candidate
Department of Economics
College of Business and Economics
West Virginia University
Kaitlyn.Harger@gmail.com
(202) 701-8428
https://sites.google.com/site/kaitlynharger/

Education

Ph.D. in Economics, West Virginia University — May 2015 (Expected)
M.S. in Economics, West Virginia University — May 2014
B.S. in Economics, Duquesne University — May 2011 (cum laude)

Research Interests

Urban Economics, Public Economics, Economics of Crime, Regional Economics

Published Papers

Hall, J.C., Harger, K.R., and Stansel, D. 2015. Economic Freedom and Recidivism: Evidence from US States. *International Advances in Economic Research*, forthcoming.
Harger, K.R., and Hall, J.C. 2015. Obedience and Income Levels. *Applied Economics Letters*, 22(2): 94-98.
Hall, J.C., and Harger, K.R. 2014. Teaching Students to do Public Choice. *Journal of Economic and Finance Education,* forthcoming.

Papers under Review

Harger, K.R. and Ross, A. 2014. Do Capital Tax Incentives Attract New Businesses? Evidence across Industries from the New Market Tax Credit. *Under second review at Journal of Regional Science*. **(Job Market Paper).**
Harger, K.R., and Young, A.T. 2014. Globalization and Income Convergence. *Under second review at Constitutional Political Economy*.

Working Papers

Harger, K.R. 2014. Bad Ink: Visible Tattoos and Recidivism.
Harger, K.R. 2014. Does Distance between Residence and Incarceration Facility Affect Recidivism? Evidence from the Florida Department of Corrections.
Harger, K.R. 2014. Correctional Officer Unions and Prison Populations.

Book Review

Harger, K. 2014. "Review of *The Toughest Beat: Politics, Punishment, and the Prison Officers Union in California*." *Public Choice* 160 (1): 279-281.

Policy Reports

Marlin, M., Scott, J., & Wolf, K., 2010. "The Grand Bargain is Dead: The Relative Costs of Ohio Private and State Government Employees" *Buckeye Institute Policy Brief.*
Wolf, K. & Davies, A, 2010. "Medical Malpractice Reform in Pennsylvania*" Commonwealth Institute Policy Brief.*

Conference Participation

American Economic Association, 2015 (scheduled): *Do Capital Tax Incentives Attract New Businesses? Evidence across Industries from the New Markets Tax Credit*
Southern Economic Association, 2014 (scheduled): *Bad Ink: Visible Tattoos and Recidivism*
Southern Economic Association, 2014 (scheduled): *Do Capital Tax Incentives Attract New Businesses?*
Urban Economics Association, 2014 (scheduled): *Do Capital Tax Incentives Attract New Businesses? Evidence across Industries from the New Markets Tax Credit*
Association for Public Policy Analysis and Management, 2014 (scheduled): *Bad Ink: Visible Tattoos and Recidivism*
Western Economic Association, 2014: *Bad Ink: Visible Tattoos and Recidivism*
Public Choice Society, 2014: *Correctional Officer Unions and Crime Policy*
Southern Economic Association, 2014: *Globalization and Income Convergence*
Association for Private Enterprise Education, 2012: *Obedience and Income Levels*

Teaching Experience

Instructor with Full Responsibilities

Business Statistics	Fall 2014	Large Lecture (200 Students)
Business Statistics	Summer 2014	Online
Principles of Microeconomics	Summer 2013	Lecture

Teaching Assistant

Graduate Macro. Theory	Spring 2014	Lecture
Principles of Microeconomics	2011, 2012, 2013	Large Lecture (340 Students)
Principles of Macroeconomics	Fall 2012	Large Lecture (340 Students)

Referee Experience

Journal of Entrepreneurship and Public Policy, *Journal of Private Enterprise*

External Fellowships, Awards, and Honors

Second Place Winner, APPAM Poster Session, November 2014
Lindau Meeting of the Laureates in Economic Sciences Award Recipient, 2014
One of only 29 students from the United States selected to attend
Horowitz Foundation for Social Policy Grant Recipient, 2013
Fewer than five percent of applicants awarded a grant
Humane Studies Fellowship Fall 2013- Present
Adam Smith Fellowship Fall 2012-Spring 2013

References

Joshua Hall
Associate Professor
Department of Economics
West Virginia University
(304) 293-7870
Joshua.Hall@mail.wvu.edu

Amanda Ross
Assistant Professor
Department of Economics
West Virginia University
(304) 293-7869
Amanda.Ross@mail.wvu.edu

Brian Cushing
Associate Professor
Department of Economics
West Virginia University
(304) 293-7881
Brian.Cushing@mail.wvu.edu